The impact of public information on financial markets

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"Market participants do not know whether to buy on the rumor and sell on the news, do the opposite, do both, or do neither, depending on which way the wind is blowing."

John Bird and John Fortune on *The Last Laugh*

Foreword

I would like to thank my advisor, Prof. Thorsten Hens, for his valuable guidance during my doctoral experience. My gratitude also goes out to other professors, in Zurich and elsewhere, for their inspiring feedback, to my older colleagues from the PhD program for great tips and advice and to my younger colleagues for not graduating before me.

As always, I honor my parents for bringing me to where I am now.

Part I

Introduction

Information is the global currency of today and nowhere is it more true than in financial markets. Specialized agencies like Reuters, Bloomberg and Dow Jones invest large sums to develop the fastest, most accurate and most reliable systems of delivering thousands of news every day to investors around the world. The sheer volume of news has long exceeded the capacity of human beings to process it manually but advances in computer linguistics and text processing open up unique possibilities for a systematic and automated analysis. Based on these advances, this dissertation deals with the impact of news announcements:

i. on the prices of stocks mentioned in the news,

ii. on the prices of other stocks, and

iii. on the broader market.

Separately, it deals with the question of whether quantifying the search for information can offer insights about investor uncertainty.

The theoretical backdrop for this kind of research is the famous Efficient Market Hypothesis put forward by Fama (1970), according to which new information is immediately impounded into stock prices. Consequently, public news should not have any predictive power for future returns and no strategy formed on the basis of public news should be systematically profitable. Empirical challenges to its validity are almost as old as the EMH itself. The roots of research on corporate announcements date back to the seminal paper of Ball and Brown (1968) and the literature on post-earnings announcement drift (PEAD) is amongst the largest in any area of accounting and finance. Similar studies have been performed for dividend initiations and omissions (Michaely, Thaler, and Womack (1995)), share repurchases (Ikenberry, Lakonishok, and Vermaelencq (1995)) as well as stock splits and reverse splits (Desai and Jain (1997), Ikenberry and Ramnath (2002)) and all have shown that returns following news announcements are, in fact, predictable.

The main limitation of earlier research is already apparent - it could only look at announcements either with a strong quantitative component or those, which *per se* had more or less clear implications for shareholder value. Otherwise, it was simply not possible to directly distinguish positive announcements from negative ones. Some authors would use the market reaction as an indirect measure (Chan (2003)) while others would avoid the problem altogether and concentrate on news volume like Mitchell and Mulherin (1994) and more recently Fang and Peress (2009). The situation changed with the popularization of automated text analysis, which in the finance literature was spearheaded by Paul Tetlock and his string of papers utilizing the "bag of words" approach to extract the fraction of negative words as a quantitative measure of linguistic content of any kind of announcement. His main findings were that the tone of today's news helps predict tomorrow's returns (Tetlock

(2007), Tetlock, Saar-Tsechansky, and Macskassy (2008)), that public news acts to resolve asymmetric information (Tetlock (2010)) and that at least some investors react to stale news (Tetlock (2011)). Linguistic tone has also been integrated into the earnings literature as a complementary dimension to (quantitative) earnings surprise and shown to independently predict PEAD and future earnings (Davis, Piger, and Sedor (2006), Engelberg (2008), Demers and Vega (2011)). A variety of methodological improvements to analyzing language have also been suggested including designing better dictionaries (Loughran and McDonald (2011)), identifying words, which were associated with price reactions in the past (Jegadeesh and Wu (2011)) as well as using purpose built software (examples are Diction and Opinion Finder) or data provided by financial news agencies, with Dow Jones and Thomson Reuters leading the market for news analytics solutions. The empirical results in this dissertation are mainly based on data from the Thomson Reuters News Analytics archive, containing all company-specific announcements, from Reuters and direct corporate news wires, for the period 2003-2011.

The first contribution of this dissertation is to show that negative news is, broadly speaking, more informative. This is on one hand apparent when the stylized model of Tetlock (2010), in which news resolves asymmetric information, is augmented to include news tone. Similarly, negative news about one company contains more information about other companies than positive news. Empirically, this translates into a larger increase in the market beta of the announcing company after negative news. This extends the results of Patton and Verardo (2012), who first suggested the link between changes in beta and learning from news, and is well explained by the tendency of companies to withhold negative news modeled by Acharya, DeMarzo, and Kremer (2011). Greater impact of negative news seems related to the fact that periods of bad financial news coincide with periods of increased interest in the economy. Using internet searches as a proxy for information search provides clear evidence of this relationship. Another interesting finding concerns the role of news agencies, which seem more successful at filtering out interesting company announcements rather than generating stories on their own. Finally, it turns out that company news does not only affect individual companies. Using a bottom-up approach to construct measures of aggregate tone and disagreement of news offers significant predictive power for index returns, realized volatility as well as the variance premium, which was suggested by Bollerslev, Tauchen, and Zhou (2009) as a measure of economic uncertainty.

In the following, a summary of the four research papers comprising this dissertation and the details of their contribution are presented individually.

”Measuring economic uncertainty and its impact on the stock market”

In this paper a novel measure of economic uncertainty based on the frequency of internet searches is proposed. Numerous models in the finance literature argue that economic agents have a preference for early resolution of uncertainty and that economic uncertainty has an impact on the stock market (see Bollerslev, Tauchen, and Zhou (2009)). On the other hand, studies in economic psychology consistently find that the typical response to uncertainty is by increasing information search (see Lemieux and Peterson (2011) and the references therein). Combining these insights, the paper attempts to capture investor uncertainty by analyzing internet search data available from Google Trends. There are two main advantages to measuring uncertainty using internet searches. The first one is the comparatively high frequency. The second one relates to the fact that the data is generated spontaneously and not by actions having directly to do with financial markets, which should limit endogeneity.

Consistent with intuition, the volume of searches for ”economy” increases after the beginning of the subprime crisis, peaks around the collapse of Lehman Brothers and decreases until mid 2011. To validate the measure further, it is compared against a peer group of established indicators of uncertainty (VIX, Variance Premium and the Yield Spread) and confidence (State Street and Shiller’s Confidence Indices). It is positively correlated with all other measures of uncertainty and negatively with two out of three measures of confidence. Of those two, one is aimed at capturing the confidence of individual and the other one of institutional investors, thus partly addressing the concern that internet searches only capture the attitudes of individual investors. Changes in the search intensity for ”economy” also appear to capture the financial impact of uncertainty in a very timely fashion. In the week following an increase in uncertainty aggregate stock returns are low but reverse in the week after. Conversely, realized volatility is high in the week after the increase and subsides in the following week. Both findings are robust and consistent with a scenario in which investors react to uncertainty first by selling risky assets and demanding a risk premium afterwards. Another advantage of using internet searches is that they are available internationally and the original results for the US can be shown to hold in several other markets as well.

”Which news resolves asymmetric information?”

The ultimate goal of this paper is to determine relevant characteristics, which increase the informativeness of news in the context of resolving asymmetric information. The departing point for the analysis is a model proposed by Tetlock (2010), in which information flows from informed traders to the uninformed ones via the publication of news. Testable predictions from this model are smaller return reversals after news days and higher correlation between abnormal turnover and absolute return on news days than on other days.

Both these effects should be especially strong after highly informative news.

The main contribution to the model is to separate two important dimensions characterizing company news: its tone and its source. The source can be either the company itself, when the announcement was published through an outlet such as PR Newswire or Businesswire, or a news agency like Reuters. Thus, at the daily frequency there can be three situations: only company news, only agency news or both. Similarly, the daily tone of news about a company can be either positive, negative or neutral, depending on how it compares to the distribution of news tone for that company in the previous quarter. The methodology is then based on comparing return reversal after news days and turnover/return correlations on news days with those on other days. The result is that only news days with both types of news, where the resulting combination is either negative or neutral produce effects consistent with the resolution of asymmetric information. One conclusion from this result is that news release by companies is not very informative unless it is picked up by news agencies. By the same token, news agencies appear more successful in selecting important direct company announcements rather than generating own ones.

However, it is not immediately clear why this selection mechanism works only for neutral and negative news. The answer is provided by looking at other news characteristics, in particular the total number of words in a news story and the number of words related to the company the story is about. The first finding here is that when companies release negative news, it contains less words related to them than positive news. In other words, good developments are presented in close association with the company, while bad ones are being explained by external factors. Agency news is significantly shorter in general and especially for negative and neutral announcements this has the effect of putting the focus back on the company and making the news more informative. For positive news, where the company is put in the spotlight anyway, this kind of simple content filtering has no further effect. The reason why positive news does not resolve asymmetric information in the first place seems related to the fact that companies are very keen to release positive news, even if it has little content, but are quite reluctant to release negative news.

"Short-term reactions to news announcements: what do investors learn from them?"

Following up on the findings that news, mainly negative news, provides useful information about the announcing companies, this paper investigates the informativeness of news about one company for other companies in the market. The basic framework for looking at this problem has been provided in Patton and Verardo (2012) model of learning from news. If news about one company contains information about other companies, then the stock price of a portfolio consisting of those other companies, i.e. the market, should move in the same direction as the stock price of the announcing company. Empirically, this should translate into an increase in the market beta of the announcing company. Interestingly, for a sample of earnings announcements the effect depends on the informativeness of news but not on the sign, that is positive and negative announcements are equally important.

The situation changes when the model is generalized to the case of voluntary disclosure, which is the main contribution of this paper. Due to the incentive structure governing the release of information by managers and the fact that investors cannot determine when managers themselves have learned the news, there will be differences in the timing of positive and negative news. In particular, positive news is always released immediately, while negative news is withheld. This is the critical difference to the case of mandatory announcements, like earnings, where the release date is fixed. From the point of view of learning across companies, this has the following implications. Given a positive news release from one company, investors have little reason to believe that other companies have similar positive news, because such news would have been released already. On the other hand, when one company releases negative news, it is quite likely that other companies also have negative news, which has been withheld for strategic reasons. This is the motivation to expect an increase in beta after negative but not positive news.

Using monthly regressions with stock beta as the dependent variable generates exactly this kind of pattern. Betas are generally higher in months with news than in other months but this effect is limited to months with negative news. Also, the volume of news has to be unusually high for the effect to be meaningful, reflecting the fact that news has become a very common occurrence. Finally, to confirm the theoretical intuition, months with earnings announcements exhibit significant increases in beta regardless of the sign of the news.

"Aggregate news tone, stock returns and volatility"

The main contribution of this paper is to construct two novel measures: the aggregate level of news tone and the aggregate dispersion of news tone. The latter is calculated as the dispersion of news tone of individual companies around the average for all firms. The novelty comes on one hand from combining the tone of millions of firm-specific news items into a single marketwide indicator and on the other hand from looking at both the first and second moment of news flow. Empirically, it can be shown that higher level of aggregate news tone is associated with higher economic activity, higher aggregate returns, and lower aggregate stock volatility, while the aggregate dispersion of news tone has the opposite effects.

There are two possible explanations for these patterns. Either aggregate measures of news flow capture high-frequency fluctuations in fundamentals or they proxy for investor sentiment. Evidence provided in the paper is consistent with the former interpretation. In particular, the aggregate level of news tone and the aggregate dispersion of news tone are highly correlated with fundamental indicators such as the Chicago Fed National Activity Index but only weakly correlated with the Baker-Wurgler investor sentiment index. However, this does not mean that news is redundant with respect to fundamentals. In fact, the predictive power for stock returns and volatility exists even after a broad range of control variables which reflect economic and financial conditions is accounted for. Moreover, especially the dispersion of news tone is a significant driver of economic uncertainty, as expressed in the variance premium of Bollerslev, Tauchen, and Zhou (2009). Thus, the paper offers evidence that news represents the "soft" part of fundamentals, reflecting the overall level and uncertainty about company information, driving rational investor uncertainty.

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Part II

Research papers

Research paper 1

Measuring economic uncertainty and its impact on the stock market

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[1] A version of this paper was published in the journal Finance Research Letters:
Dzielinski Michal (2012), "Measuring economic uncertainty and its impact on the stock market", Finance Research Letters, 9(3), 167 - 175

Abstract

This paper proposes a novel measure of economic uncertainty based on the frequency of internet searches. The theoretical motivation is offered by findings in economic psychology that agents respond to increased uncertainty by intensifying their information search. The main advantages of using internet searches are broad reach, timeliness and the fact that they reflect actions, rather than words, which however are not directly related to the stock market. The search-based uncertainty measure compares well against a peer group of alternative indicators and is shown to have a significant relationship with aggregate stock returns and volatility.

1.1 Introduction

Numerous models in the finance literature argue that economic agents have a preference for early resolution of uncertainty and that economic uncertainty has impact on the stock market (Bansal, Khatchatrian, and Yaron (2005), Boguth and Kuehn (2009) and Bollerslev, Tauchen, and Zhou (2009) to name just a few). On the other hand, studies in economic psychology consistently find that the typical response to uncertainty is by increasing information search (see e.g. Lemieux and Peterson (2011) and the references therein). Thus, it would seem natural to measure the uncertainty of investors by analyzing their search behavior. In this paper I argue that the frequency of internet searches reported by Google Trends can be used to appropriately capture the investor uncertainty about the state of the economy and that it has implications for aggregate stock returns and volatility.

The departing point is the conjecture more uncertain investors seek information more intensively and that this can be represented by the volume of internet searches. The first part of the argument is substantiated by the psychological evidence mentioned above. The main task here is identifying the relevant subset of all possible searches. The second part has to do with the spread and centralization of internet searches. Internet penetration in developed countries now exceeds 75% of households according to www.internetworldstats.com and its role for various aspects of life but especially information exchange and retrieval is unquestionable. Willingly or not, every internet user leaves behind data on what she or he was looking for every time when using a search engine. If analyzed systematically and on a large scale, such data would be ideally suited for tracking information seeking activities in the real world environment. This has become realistic after Google revolutionized internet search technology in the late 90's, becoming the biggest search engine by June 2000, first as measured by the number of indexed pages, and soon after also by the number of users. In recent years it has consistently accounted for an estimated 70% of global search traffic. Therefore, patterns of searches obtained by Google have a serious claim on representativeness. With the launch Google Trends in 2006 this vast universe of data became publicly available. Google Trends makes it possible to track the relative popularity of any given search term over time. The dataset goes back to 2004 and is updated weekly. It is also scaled by the total search traffic, so as to conceal the actual number of Google users, and presented in the form of a search volume index (SVI). In 2008 a sister application was launched under the name Google Insights for Search, which includes a useful extension,

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BR - Barron's Confidence Index
OYC_{inst}, OYC_{ind} - Yale School of Management Stock Market Confidence Index for institutional and individual investors respectively
ST - State Street Confidence Index
SVI - Search Volume Index from Google Trends
VP - variance premium

allowing filtering the results by category to determine e.g. what users searching for "apple" were actually interested in (two of the over 20 categories are "Computers & Electronics" and "Food & Drink"). Based on these two sources I construct a measure to capture the information seeking of investors and thus their degree of uncertainty.

The are two main advantages to measuring uncertainty using internet searches. The first one is the comparatively high frequency. The second one relates to the fact that the data is generated spontaneously and not by actions having directly to do with financial markets, which should limit endogeneity. One objection often raised against this kind of measures is that they can, at best, capture the behavior of individual, less sophisticated investors only. I try to address this concern directly by comparing the Google Trends measure to a peer group, which also includes indicators specifically designed with institutional investors in mind. Moreover, focusing on individual investors, even if true, does not make the measure useless. Such investors can also have a significant impact on the stock market, especially in volatile periods.

Internet search data have already found applications in the finance literature. They were used to predict sales (Choi and Varian (2009b)), jobless claims (Choi and Varian (2009a)), flu outbreaks (Dukic, Lopes, and Polson (2009)), individual investors' demand and IPO returns (Da, Engelberg, and Gao (2011)) as well as modeling volatility asymmetry (Dzielinski, Rieger, and Talpsepp (2011)). This paper bears most direct resemblance to Da, Engelberg, and Gao (2010) where principal component analysis is applied to a number of economy-related search terms and the resulting index is said to capture investor sentiment. Though some of the results point in the same direction, the motivation is different. By calling their index a sentiment measure, the authors necessarily imply a degree of irrationality. In my approach, an increase in searches is a symptom of increased uncertainty, which can be perfectly rational.

1.2 Internet searches and economic uncertainty

The key issue is how to filter out the relevant content of internet searches, which in the case of Google Trends boils down to selecting appropriate keywords. One thing to avoid is hindsight bias. Today it may be well-known that recession, oil price and subprime were topics of great interest to investors over the past few years (unreported results actually show that an indicator based on a combination of those does a pretty good job) but back in 2005 the choice would have probably been different. The problem is to find a keyword that is general and time-invariant, while maintaining sufficient relevance. The word "economy" itself seems to be a parsimonious solution. It is definitely sufficiently broad to encompass all possible sources of economic uncertainty, including the three mentioned above, and also to be time independent. On the other hand it appears specific enough to contain noise that is either relatively small or at least constant over time because it is not used to describe any other concept, whose popularity might be correlated with the one of interest (this might be the case for instance with the word "depression"). "Economy" should also capture searches for related words, like "economic" or "economies" rather well. In particular, there is no reason suspect that the propensity of users to search for either "economic" or "economy" is driven by different factors. Indeed, the time series of search volume for "economy" and "economic" track each other very closely (not shown) and the correlation between them is 0.94. Other versions of the main keyword, like "economies", are associated with negligible search volumes.

If the assumption of constant noise is correct, the trend component should represent the relevant part of information seeking. I isolate it by dividing the current value by the value of the corresponding week one year ago, which also helps deal with the observed seasonality (Figure 1a). The dynamics of this modified measure is shown in Figure 1b, it is relatively stable until mid 2007 and increases sharply afterwards. The peak coincides with the bankruptcy of Lehman Brothers, after which a gradual return to pre-crisis levels takes place. The last months of the sample show a renewed increase in the index, indicative of the sovereign debt crisis that unsettled the markets.

I also compare the year-on-year series obtained from Google Trends with the SVI for "economy" obtained from the Google Insights "Finance & Insurance >> Investment" category. The category assignment is performed based on factors like other keywords used in the search, other searches performed before and after etc. and should reflect the context of the searches. Thus, the comparison should verify the initial intuition that year-on-year changes capture the relevant component of search dynamics for "economy". The two series indeed appear very similar and are also highly correlated ($\rho = 0.57$) though the Google Insights SVI is more volatile. Why not use the Google Insights directly in the analysis then? For one, it is somewhat less convenient to handle due to the fact that each time series is scaled to its peak (fixed at 100), so in ongoing applications rescaling would be necessary whenever a new peak appeared. More importantly, it turns out that the Google Trends year-on-year series actually significantly leads the Google Insights series with quite a large R-squared, as documented in Table 1. The likely reason is the slight shift in the weekly time window used for computing the SVI values, which is Monday-Sunday for GT and Sunday-Saturday for GI. Therefore, the Sunday, which still contributes to the current week for GT is already part of the next week for GI. Therefore, while acknowledging the important corroboration provided by Google Insights, I only refer to the Google Trends year-on-year SVI for "economy" (GT_{econ}) in further analysis.

There are two other options in the data presentation, which are important to mention here. The first one is the regional filter, based on the *origin* of the query determined from the user's IP address. For the initial analysis I use the S&P500 as the financial universe and to limit the confounding influence of searches from parts of the world unrelated to the US stock market, I only consider those originating in the US itself, which implicitly assumes that only domestic investors impact the stock market. However, it is not a significant limitation in practice since the global SVI for "economy" does not fundamentally differ from the US one. The other, more important, option concerns how the data are scaled, either to a fixed or relative reference frame. The first approach applies the average search traffic in a fixed time period (generally January 2004) as a benchmark value, while otherwise the average for the whole specified time period is used. This aspect is again important in the context of the hindsight bias, since the average for the whole period is something known only at the end. Therefore, I always use fixed scaling.

I compare the measure derived from search volume to other measures of uncertainty or confidence, which are available at least at monthly frequency. The expectation is to see a positive correlation with the former and a negative correlation with the latter type. Based on their methodology, those other measures can be put into one of two groups. The first group aims to investigate investors' opinions directly, by means of a survey. A prime example is the "One-year confidence index" published every month by the Yale School of Management, based on a sample of US institutional (pension fund managers) and wealthy individual investors. The index reflects the fraction of participants expecting a strictly positive return on the Dow Jones Industrial Average over the following 12 months averaged over a rolling window of six months. It is calculated separately for institutional and individual investors.

All other measures fall into the second group and employ some kind of measure of market activity to proxy for uncertainty or confidence. The most famous is probably the VIX index of implied volatility, often described as "investors' fear gauge". Another example is the Barron's Confidence Index, defined as the ratio of yields on high vs medium grade corporate bonds with higher values (i.e. tighter spreads) indicating higher confidence. A different approach is taken by State Street, the world's biggest institutional custodian. Using unique data on asset flows it defines a proprietary confidence index, whereby shifts in institutional holdings towards riskier assets indicate rising confidence. In the finance literature, an interesting measure was developed by Bollerslev, Tauchen, and Zhou (2009). It is based on the spread between forward-looking implied variance (derived from the VIX) and backward-looking realized variance. The higher this so-called variance premium (VP), the higher the uncertainty.

The survey-based measures deserve praise for directness but they are often criticized for limited scale (sample size) and possible problems with the honesty of the answers. On the other hand, the market-based measures are based on actions (this argument is especially underscored by State Street) and have a large scale but these actions are likely to be affected by many factors other than the one in question. GT_{econ} seems to connect the best of both: it is direct yet based on actions rather than statements, so honesty is not an issue and the scale is virtually unlimited.

Table 1.2 presents summary statistics of all the measures as well as correlations between them. Only two of the measures from the GT_{econ} peer group are readily available at the weekly frequency, so I also compute the monthly GT_{econ} for reference. It is aggregated from weekly values by taking simple averages. Whenever a week is split, it is included in the later month. The two One-year confidence (OYC) indices and the State Street (ST) confidence index are taken directly from the websites of their respective providers. The Barron's (BR) confidence index (or actually its inverse) is approximated using the yield spread between Moody's Baa and Aaa corporate bond indices obtained from Bloomberg. I also compute monthly averages of the weekly values to compare with other measures. Weekly and monthly values of the VIX index are from Datastream. Finally, I am grateful to Hao Zhou for making the monthly variance premium data available online. The sample period is Jan 2005 - Jun 2011, except the variance premium, which is available through Dec 2010.

The most volatile measure is the variance premium (mostly because of extreme values registered during the peak of the financial crisis) followed by the VIX and GT_{econ}. Other measures fluctuate comparatively little. The correlations first of all generally confirm that it is justified to consider confidence as the opposite of uncertainty because the two types of measures are consistently negatively correlated with each other. Furthermore, the correlations support GT_{econ} as a reasonable measure of uncertainty. It is positively and significantly correlated with all other measures of uncertainty, as well as significantly and negatively correlated with two of the three measures of confidence. The only exception is OYC_{inst} and the initial reaction might be to say this means that Google Trends has relevance for the behavior of individual but not institutional investors. However, the two measures of institutional confidence (OYC_{inst} and ST) are also virtually uncorrelated with each other. One way to explain this puzzling fact is the discrepancy between words and deeds mentioned before. However, even assuming both measures yield honest results it is possible that institutional investors remain confident about the long term outlook, captured by the OYC measure, while being uncertain right now, as depicted in current portfolio flows underlying the State Street index. This would also explain why the GT_{econ} measure is positively correlated with OYC_{inst}. For individual investors, both short and long term would seem to be tied together (no correlation of OYC_{ind} with OYC_{inst}, significant and positive with ST) which is consistent with them following a simpler, extrapolative market heuristics. In this context, the correlations between GT_{econ} and the three measures of confidence lend further support to saying that GT_{econ} captures uncertainty of both types of investors.

To confirm the initial findings, I regress aggregate stock returns on changes in the uncertainty measure. Using changes captures short-term fluctuations in uncertainty (Figure 1c), which should affect short-term returns. The regression is performed on weekly basis and includes changes in the two other measures of uncertainty available weekly and the past return as control variables. The Google search frequencies are measured on a Monday-to-Sunday basis, which is consistent with investors using information from the weekend during the following week. To avoid overlaps during the weekends, returns are calculated Monday-to-Monday using opening prices of the S&P500 index:

$$Ret_t = \beta_0 + \beta_1 \cdot \Delta GT_{econ,t-1} + \beta_2 \cdot \Delta BR_{t-1} + \beta_3 \cdot \Delta VIX_{t-1} + \beta_4 \cdot Ret_{t-1} + \epsilon_t \qquad (1.1)$$

The significance of $\widehat{\beta_1}$ in Table 1.3 shows that internet searches do indeed have some exogenous merit in measuring economic uncertainty or otherwise their impact would have been subsumed by the VIX. This result is consistent with the findings of Da, Engelberg, and Gao (2010). The economic impact is also large - a one standard deviation change in the index is associated with a drop in the weekly return of around 0.65%.

One concern relates to $\widehat{\beta_1}$'s negative sign, which seems to run counter to what is generally postulated as the impact of uncertainty, namely to *increase* future (expected) returns as investors demand an uncertainty premium. However, increasing expected returns requires an adjustment period in which prices have to fall, resulting in negative returns. ΔGT_{econ} could capture this adjustment thanks to its comparatively high frequency. An indication that this is the case is given by the fact that the initial negative returns appear to reverse in week $t+1$.

A much clearer relationship emerges between ΔGT_{econ} and future realized volatility. Daily values of realized volatility for the S&P500 index, computed from high frequency returns, are taken from Oxford-Man Institute's Realized Library. At the time of writing the downloadable dataset ends in February 2009. Weekly values are computed simply as the sum of the daily values within a given week. To control for persistence, first differences of logged weekly values are used in the regression, the right hand side is exactly as in Eq. 1. Consistent with the adjustment argument, volatility is high in the week following an increase in uncertainty and dies down in the week after that. The effect is especially remarkable given that it is not neutralized by implied volatility. Tracking internet searches would thus appear as a complimentary way to capture the uncertainty of those (probably less sophisticated) investors who do not have access to the options market but can still affect the behavior of equity indices.

The second concern is about the impact of the financial crisis, which covers a significant part of the sample period. To investigate it, I expand Eq. 1 by a dummy variable indicating the crisis period and also interact it with all other variables, particularly ΔGT_{econ} to see how much they are affected. The dates of the financial crisis are necessarily chosen arbitrarily, since there is no consensus when exactly the crisis happened, or in fact whether it is still happening. On one hand, the chosen dates reflect the period of extreme fluctuations of all variables, which is most likely to skew the regression results towards significance. On the other hand, shifting the starting and end points by several months does not change the conclusions (not reported). The regression equation therefore becomes:

$$Ret_t = \beta_0 + \beta_1 \cdot \Delta GT_{econ,t-1} + \beta \cdot Controls + \gamma_0 \cdot Z + \gamma_1 \cdot Z \cdot \Delta GT_{econ,t-1} + \gamma \cdot Z \cdot Controls + \epsilon_t \quad (1.2)$$

where:

$$Z = \begin{cases} 1 & \text{between May 2007 and June 2009} \\ 0 & \text{otherwise.} \end{cases}$$

Panel B of Table 1.3 gives evidence that the explanatory power of the uncertainty measure for future returns is indeed much higher during the financial crisis. This is understandable given that uncertainty is likely to be at its highest (and most influential) during periods of market turmoil. It is also when an indicator of uncertainty is most useful. The relationship to future volatility is by contrast virtually unaffected by the crisis, especially at the shorter horizon. Especially this finding gives further support to measuring economic uncertainty based on search behavior.

The global reach of internet and Google's search engine makes an international comparison compelling. Following the structure of the regional filter in Google Trends it is based on search volume for countries and the most popular indices of the respective stock exchanges. The problem of considering only domestic investors is likely to become more severe for smaller, open exchanges and a better idea for future applications could be to take an average of the SVIs from different countries weighted by the presence investors from those countries have on that stock exchange. However, domestic investors should also account for part of the variation in returns, so as a first validity check for using internet searches to measure uncertainty in different countries this crude approach is sufficient.

Another issue, specific to the regional analysis, is language. The Google Trends interface does include a breakdown of the search volume by languages but this is misleading as it only relates to the language version of the Google site where the query was initiated and not the language of the query itself. For instance the resulting SVI for "economy" for Germany and with language set to German only reflects the fact that some users in Germany went to google.de (rather than google.com) and searched for "economy" from there. However, comparing search volumes reveals that German users searching for "economy" are just a small fraction of those using the German equivalent term "Wirtschaft". Therefore, to maintain representativeness I use the local language equivalent (also for Japan).

Results in Table 1.4 offer moderate support to the usefulness of the GT_{econ} measure across countries especially with respect to volatility and in times of economic turbulence. The latter is not necessarily a big drawback because that is also when uncertainty itself is most influential. The magnitude of the estimated parameters is always larger for the crisis period but the estimates are also very noisy. This might on one hand reflect lower precision of Google search data for those countries or the fact that investors in those countries search for something else than "economy" or its direct translation. In the case of UK, which is the only country with no significant relationship at all, it might also reflect the relatively large involvement of foreign investors in that market.

1.3 Conclusions

The results of this study successfully establish a novel measure of uncertainty about the state of the economy, based on the volume of internet searches for the word "economy". The main appeal of using internet searches is that they are generated through the spontaneous behavior of agents and so have interesting signalling properties. The underlying intuition derived from economic psychology is that a higher level of uncertainty about the economy increases the demand for information, which should be reflected in higher volume of internet searches with economy as their topic. Consistent with this intuition, the volume of searches for "economy" increases after the beginning of the subprime crisis, peaks around the collapse of Lehman Brothers and decreases until mid 2011. It is positively correlated with alternative measures of uncertainty and negatively with measures of investor confidence, both individual and institutional. It also appears to capture the financial impact of uncertainty in a very timely fashion. In the week following an increase in uncertainty aggregate stock returns are low but reverse in the week after. Conversely, realized volatility is high in the week after the increase and subsides in the next week. Both findings are robust and consistent with a scenario in which investors react to uncertainty first by selling risky assets and demanding a risk premium afterwards.

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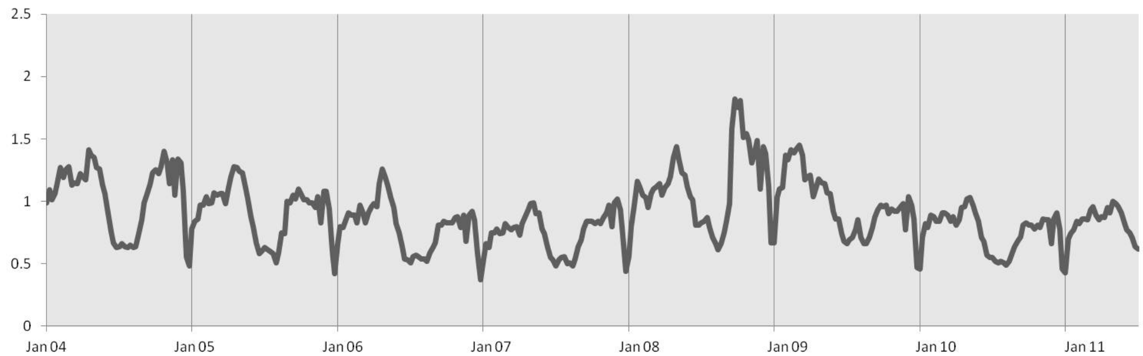
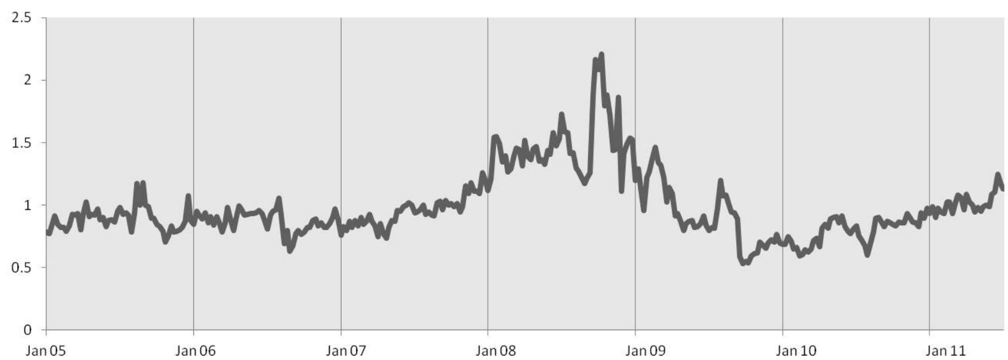
Figure 1.1: The evolution of Google searches for "economy" in the US.

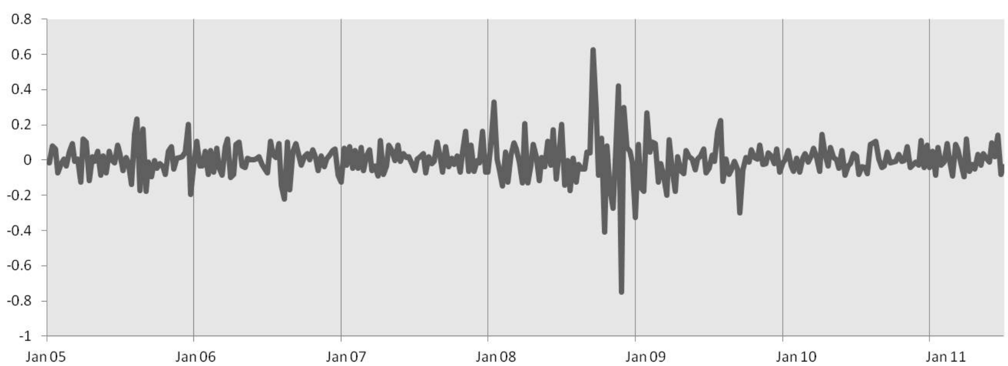
The figure presents the raw Search Volume Index (SVI) for "economy" in the US (1a) as well as two transformation used to proxy for uncertainty in the paper:
- the "year-on-year" series computed by dividing each weekly value by the corresponding value from one year ago, which deals with seasonality of the raw series (1b)
- the differenced "year-on-year" series, representing weekly changes in uncertainty (1c)



(a) SVI for "economy" (Google Trends)



(b) Year-on-year SVI for "economy" (Google Trends)



(c) Weekly changes in the year-on-year SVI for "economy" (Google Trends)

Table 1.1: Comparison of the two internet search-based uncertainty measures.

GT_{econ} is the year-to-year Google Trends index of the search volume for "economy" in the US. GI_{econ} is the Google Insights index of the search volume for "economy" in the US, restricted to the "Finance&Insurance >> Investment" category. In the vector autoregression analysis, each row represents the equation for the respective variable with the constant and lagged parameters given in columns. The sample period is Jan 2005 to Jun 2011.

Panel 1: descriptive statistics						
	Mean	Std. dev.	Correlation			
GT_{econ}	0.99	0.27	0.57			
GI_{econ}	0.17	0.10				
Panel 2: VAR analysis						
	Const. (t-stat)	$\mathrm{GT}_{econ,t-1}$ (t-stat	$\mathrm{GI}_{econ,t-1}$ (t-stat)	$\mathrm{GT}_{econ,t-2}$ (t-stat)	$\mathrm{GI}_{econ,t-2}$ (t-stat)	adj.-R^2(%)
GT_{econ}	0.06**	0.78***	-0.04	0.13*	0.20*	86.0
	(2.53)	(14.2)	(-0.38)	(1.81)	(1.72)	
GI_{econ}	-0.01	0.19***	0.59***	-0.09**	0.14**	69.0
	(-0.78)	(6.40)	(10.9)	(-2.45)	(2.19)	

Table 1.2: Internet search-based uncertainty measure in the context of other measures of uncertainty and confidence.

The table compares the measure of uncertainty derived from Google search volumes to other measures based either on investor surveys or market activity. These other measures are:
BR - yield spread of Baa over Aaa bonds (inverse of the Barron's Confidence Index)
OYC_{inst}, OYC_{ind} - Yale School of Management Stock Market Confidence Index for institutional and individual investors respectively
ST - State Street Confidence Index
SVI - Search Volume Index from Google Trends
VP - variance premium of Bollerslev, Tauchen, and Zhou (2009)
* denotes correlations significant at 5% level.

	Uncertainty measures							Confidence measures		
	weekly			monthly						
	$GT_{econ,w}$	BR_w	VIX_w	$GT_{econ,m}$	BR_m	VIX_m	VP	OYC_{inst}	OYC_{ind}	ST
Panel A: summary statistics										
Mean	0.99	1.23	21.34	0.98	1.23	21.62	19.79	79.00	79.26	103.95
Std. dev.	0.27	0.12	11.38	0.27	0.12	11.60	31.85	3.93	4.67	9.18
Panel B: correlation matrix										
	1.00	0.38*	0.55*	1.00	0.53*	0.59*	0.35*	0.24*	-0.51*	-0.40*
		1.00	0.78*		1.00	0.69*	0.10	0.06	-0.43*	-0.37*
			1.00			1.00	0.50*	0.11	-0.62*	-0.59*
							1.00	0.04	-0.25*	-0.31*
								1.00	0.03	-0.05
									1.00	0.45*
										1.00

Table 1.3: Changes in uncertainty and aggregate market returns and volatility.

The dependent variable is the return on the S%P500 index in week t and $t+1$ and the respective weekly realized volatility. The impact of the financial crisis is also considered. t-statistics are computed using the Newey-West correction for up to 4 lags. *, ** and *** denote significance at the 10%, 5% and 1% level respectively.

Panel A: unconditional results				
	Ret_t	Ret_{t+1}	ΔRV_t	ΔRV_{t+1}
ΔGT_{t-1}	-0.0604***	0.0097	1.18***	-0.63**
	(-3.12)	(0.38)	(5.50)	(-2.19)
No. obs.	338	337	216	215
Adj. R^2 (%)	6.1	0.1	19.9	2.8

Panel B: conditioning on the financial crisis								
	$Z=0$	$Z=1$	$Z=0$	$Z=1$	$Z=0$	$Z=1$	$Z=0$	$Z=1$
ΔGT_{t-1}	-0.0194	-0.0807***	-0.0237	0.0276	1.21**	1.14***	-0.55	-0.65**
	(-1.33)	(-3.29)	(-1.35)	(0.80)	(2.94)	(4.69)	(-0.86)	(-2.02)
No. obs.	113	225	113	224	121	95	120	95
Adj. R^2 (%)	8.4		1.4		19.5		3.6	

Table 1.4: Impact of uncertainty across countries.

The same regression as before is performed using returns and realized volatilities of major indices in five countries other than the US (Australia - ASX200, Canada - TSX, UK - FTSE100, Germany - DAX30, Japan - Nikkei225). t-statistics are computed using the Newey-West correction for up to 4 lags. *, ** and *** denote significance at the 10%, 5% and 1% level respectively.

	Australia	Canada	UK	Germany	Japan
			Returns		
Z = 0	-0.0215**	-0.0057	-0.0005	-0.0106	-0.0454**
	(-2.20)	(-0.67)	(-0.07)	(-0.89)	(-2.39)
Z = 1	-0.0333**	-0.0418	-0.0695	-0.0244	-0.1202
	(-1.95)	(-1.41)	(-1.27)	(-0.79)	(-1.36)
No. obs.	339	339	339	339	339
Adj. R^2 (%)	3.7	2.6	7.1	4.7	4.8
			Realized volatilities		
Z = 0	0.47	0.35**	-0.05	0.86***	0.14
	(1.27)	(2.01)	(-0.11)	(2.32)	(0.25)
Z = 1	-0.13	1.00**	0.66	1.31**	2.81***
	(-0.39)	(2.23)	(1.52)	(2.22)	(3.58)
No. obs.	216	216	216	216	216
Adj. R^2 (%)	15.3	9.8	12.2	16.8	15.7

Research paper 2

Which news resolves asymmetric information?

Michal Dzielinski

Abstract

The aim of this paper is to advance the understanding of the role public news plays in resolving asymmetric information. Based on three testable predictions developed in earlier literature and a large dataset of newswire announcements, two novel findings are established. First of all, the resolution of asymmetric information occurs mainly on news days featuring announcements both by companies and news agencies. Coverage by a news agency substitutes for the effect of high turnover, highlighting the important role of news agencies in selecting newsworthy company news. Secondly, positive news does not resolve asymmetric information on average, while neutral and negative news does. The mechanism behind this result seems to be the "positivity bias" in company news and the failure or unwillingness of news agencies to properly account for it. The fact that news agencies only fail to correct the bias in very positive company news links to some recent findings in the exercise of news "spin" in order to generate positive coverage.

2.1 Introduction

The motivation for this study are recent findings linking public financial news to the resolution of asymmetric information. This is a very important aspect of the news and financial markets literature, because it addresses the question of whether public news is informative, in the sense of making information initially possessed only by insiders available to everyone. Tetlock (2010) proposes a stylized model reflecting exactly this link, in which signals about future payoffs flow from informed investors, who are however vulnerable to liquidity shocks, to the uninformed ones via the release of public news. After seeing the news and extracting the signal, previously uninformed investors are more willing to provide liquidity, because they can infer the size and sign of the informed traders' shock and its impact on expected returns. The model offers four testable hypotheses: i) returns after news days are positively autocorrelated; ii) the effect is even stronger after news days characterized by high turnover and iii) the correlation between absolute return and volume is higher on news days than other days iv) the price impact of order flow should be smaller on news days. These predictions can be confirmed empirically, in particular the findings for the first two are that reversals over ten days following news days are significantly smaller than after no-news days and high turnover reduces reversals even more. In this paper they can be shown to remain valid also during the recent crisis, underscoring the importance of news in financial markets.

This paper further argues that news should not be treated as a homogenous group, like it was done in earlier literature and makes two significant contributions to the analysis of news and asymmetric information. The first one consists in considering not only stories from news agencies, Reuters in this case, but also those 'wire' news, which are released directly by companies to communicate all kinds of material developments. In fact, many of the agency announcements are closely related, at least in time, to such direct company communication, suggesting it is an important basis also for financial reporting. As such, it is the most comprehensive news dataset used in the finance literature. The ability to combine stories from different sources leads to the first novel empirical result of the paper that only news days featuring stories both from the company and the news agency are followed by significantly smaller reversals compared to the no-news case. This finding offers an important insight into the role of news agencies in financial markets - they contribute to the resolution of asymmetric information by selecting newsworthy corporate announcements to report on rather than by generating influential stories themselves. This conclusion is supported by two auxiliary findings, the first of them being the apparent substitutability of news agency coverage and high turnover, which is often considered to be a proxy for informativeness. High turnover, while significantly decreasing reversal after days with news only from companies or agencies, has no effect on reversal after days with news from both sources. The other piece of evidence comes from studying the abnormal return-turnover correlation around news days, which peaks already on day $t-1$ if day t is a news day with only agency news. This suggests that the market reacts already ahead of such news, which necessarily makes them less informative.

The second contribution lies in analyzing the language of the news stories in order to determine whether positive and negative news performs differently with respect to the resolution of asymmetric information. Especially after the beginning of the recent crisis there has been much discussion about the presence of "positivity bias" in financial news, due to companies aiming to present themselves favorably and news agencies colluding with the companies in order to maintain privileged access to information. A substantial skew towards positive stories can indeed be found, especially for stories published directly by companies, and it is also true that positive news days are followed by reversals comparable to no-news days, suggesting positive news resolve little of the information asymmetry. Furthermore, while combining company and agency news does significantly impact reversal when the resulting combination is either neutral or negative, this is not true if the combined news is positive. Following up on this finding highlights another important role for news agencies, besides story selection, which is unwinding the bias in corporate announcements. Comparing the tone of stories released by companies and news agencies on the same day shows that the tone of the latter stories is significantly more negative. However, this does not happen if the company news is very positive. This effect seems well explained by looking at other characteristics of positive and negative news. Negative news from companies is longer than positive and contains less words deemed relevant to the company itself. This is consistent with companies identifying positive developments with own actions and attempting to "explain" negative ones with external factors. Agency news on the other hand is much shorter in this case and contains more words related to the company. It seems that by filtering out the unrelated content news agencies bring the negative content to the spotlight and make the news more informative. It is apparent why this simple "shortening" mechanism cannot work when the original company announcement is positive as a whole. It also suggests that financial media is reluctant to interfere with the release of positive news about companies and also appears to explain why positive news, even from combined sources, does not resolve asymmetric information.

The above contributions add to the broader literature on the impact of public news on financial markets by linking the studies of Tetlock (2010), and also Chan (2003) and Gutierrez and Kelley (2008), which consider news and reversals but do not distinguish on news tone with the pioneering studies of Tetlock (2007) and Tetlock, Saar-Tsechansky, and Macskassy (2008), where the linguistic analysis of text was first applied to financial news.

Another contribution to this literature is by utilizing an innovative dataset of machine-processed news supplied by Reuters. Earlier studies using this data have focused on three topics. Groß-Klußman and Hautsch (2011) looked at the instantaneous impact of public news using high-frequency data. They find strong responses in volatility, volume and liquidity measures and a mixed picture for returns. Storkenmaier, Wagener, and Weinhardt (2012) also construct measures of intraday liquidity and trading activity but focus on comparing the averages for negative and positive news days to no-news days. They find that liquidity is significantly lower on negative news days but not significantly higher on positive ones. Trading activity always increases on news days, regardless of the sentiment. Finally, Sinha (2010) uses news sentiment to calculate monthly sentiment scores for individual stocks, which are then used to construct ”news momentum” portfolios. The use of such machine learning approaches adds to the line of papers, such as Loughran and McDonald (2011), Jegadeesh and Wu (2011) and Graf (2011), which aim to move beyond counting general negative words in gauging the content of financial news.

By explicitly separating news originated by news agencies and by companies themselves, the paper also relates to two further strands of the media and finance literature. One of them, represented by Solomon (2012), is concerned with news ”spin” exercised by some companies, which hire investor relations firms apparently in order to promote widespread coverage of positive announcements. Although I do not include the role of IR firms in my analysis, the finding that news agencies do not seem to correct downwards the tone of clearly positive company announcements (while doing exactly that for less positive announcements) also hints at the tendency of financial media not to interfere with good news about companies. The other strand analyzes the role of financial media at a more general level, with particular focus on whether media or specific journalists can causally affect trading through their publishing, see Engelberg and Parsons (2011) and Dougal, Engelberg, Garcia, and Parsons (2012). My results, especially the fact that agency news are significant only when coupled with company news, hints at the sources of any impact media can have on the stock market - the selection of newsworthy corporate announcements (and perhaps modifying their language) rather than the generation of original news.

The rest of the paper is organized as follows: the next section describes the data, in particular the news announcement data, and the sample used in this study in more detail. Section 3 presents the methodology and the results of the baseline analysis of the three model predictions. Section 4 investigates the role of news tone, news source and some further news characteristics in resolving asymmetric information. Section 5 concludes.

2.2 Data and sample selection

I analyze a large dataset of 2.5mln news stories related to over 4'000 US companies over the period 2003-2011. The source of this data is the Thomson Reuters News Analytics archive, which also contains complete information from third party feeds such as PR Newswire and Business Wire, which are important outlets for companies to communicate directly with investors, bypassing financial journalists. Globally, the archive contains almost 13mln news announcements for more than 20'000 stocks, roughly 57% of them attributable to Reuters and the rest to direct corporate outlets. To simplify language, all news released by companies directly to investors are referred to as 'wire' news (shorthand for PR Newswire, BusinessWire and other popular outlets) and all news published on one of the Reuters services as 'agency'. Therefore, I assume that news published by Reuters is representative for news published by news agencies in general.

Based on the exchange codes for NYSE, NASDAQ and AMEX (.N, .O and .A respectively), the US market contributes 34% of the newsflow, making it by far the biggest market for news. Interestingly, while the US share of wire news decreases over time, it actually increases for agency news, as shown in Figure 2.1. The fact that the US share of agency news peaks in 2008 suggests that this interest was to some extent related with the US being at the center of the financial crisis. However, in 2011 it is still considerably larger than the US share of global companies.

[Figure 2.1 about here]

The main motivation for using the News Analytics archive, apart from the very comprehensive and accurate coverage, is the rich metadata supplied with every news announcement. This metadata is the output of a detailed linguistic examination developed and maintained by Thomson Reuters itself. It includes descriptive information such as the precise timestamp, the headline, the source, the number of companies mentioned and their identifiers as well as the total length (in words and in sentences) of the news item. It is worth mentioning at this point the common practice among news agencies of releasing news in stages rather at once. Thus one would expect a single story to consists of an alert (usually just the headline), a main article and possibly one or more appends, all of which would be separately recorded in the archive due to having different timestamps. Importantly, each new part of the story is not issued on a standalone basis but rather stitched (or appended) to the previously existing body and the complete text is released again. Therefore, statistics like the number of words reflect the length of the story from the beginning up to its current state and not just the most recent addition. Individual items making up a single story can be linked together using the so-called PNAC number and Figure 2.2 plots the count and average length of individual news items according to their position in the above mentioned cycle, as well as per story basis.

[Figure 2.2 about here]

Comparing panels A and B, one can see the difference between the publishing practices of companies and news agencies. Wire news almost always is issued in one piece, reflecting the fact that it is for the most part prepared in advance. Agency stories on the other hand consist of 2.5 items on average and generally include at least one alert and one article. They are also considerably shorter than wire news. The above insights are relevant because the number of individual news items has previously been suggested as a proxy for the thoroughness and informativeness of a given news story, see Tetlock (2010).

The most important metadata is analytical and focuses on trying to grasp the content of the announcements. The key variables in this respect are the tone of the announcement and its relevance for a particular company. The relevance score, which is between 0 and 1, measures the strength of the association between the news item and the company, where the maximum relevance is generally reserved for news where the company is mentioned directly in the headline. The tone is a discrete variable with three possible values: negative (-1), neutral (0) or positive (+1). Neutral means that neither a negative not a positive assignment could be made with sufficient confidence. The measurement of relevance and of the news tone is performed fully automatically. The algorithm developed for this purpose by Thomson Reuters belongs to the next generation of text processing tools and goes beyond the "bag of words" approach and aims to extract syntactic relationships, identifying words as subject, predicate or object. Such algorithms can be either *deductive*, meaning they follow explicit rules on how to parse the text which have to be defined in advance, or *inductive* in which case a learning set of evaluated texts has to be supplied from which the algorithm attempts to read the rules applied to all subsequent items. Both approaches can also be combined and improvements in accuracy achievable by introducing syntax are significant. Also, contrary to what is sometimes said, syntactic approaches are no more subjective than "bag of words". In fact, surveys of methods of content analysis assign all of them to the family of "supervised approaches", indicating human involvement in their design. This is because the dictionaries, which are behind any "bag of words" analysis have to be created by humans. Even inductive algorithms offer a fair degree of inter-subjective reliability, because the learning sets are always evaluated by more than one person and the results of learning are only accepted when the agreement between the instructors and the machine but also among the instructors themselves reaches a certain, appropriately high threshold. In the News Analytics archive this is reflected by three ”tone probability” scores, which show how likely each news item was to receive one of the three tone labels: positive, neutral or negative (the one assigned is simply the one with the highest probability).

Breaking down the stories by tone, year and source reveals a significant bias among the wire announcements, with positive stories accounting for 60% of all stories even during the financial crisis. There is a slight increase in the number of negative stories over time but it does not even keep up with the overall growth in news volume. Agency stories by contrast are more balanced and more reflective of the economic cycle, with negative stories dominating during bear market periods. There is also a marked increase in the number of neutral stories over time, possibly reflecting one of the recent criticisms of financial media that they focus on aggregating third-party opinions instead of contributing opinions themselves. The analysis of aggregate news flow thus motivates treating agency and wire news separately, due to the important differences found between the two categories.

[Figure 2.3 about here]

Ultimately, I am interested in news about individual stocks for which it is possible to obtain pricing and accounting information. Therefore, I match Reuters Instrument Codes (RICs), which are the primary identifier in the news dataset, to CRSP permanent numbers (PERMNOs), based on historical CUSIPs. Due to changes in either CUSIP or RIC, as a result of corporate actions, listing on a different exchange etc., multiple matches are possible. I only accept those, where the same PERMNO is matched to more than one RIC but not the other way round. This is to avoid double-counting news by assigning it to two or more companies. Following this procedure, I am able to match roughly 80% of the distinct RICs and stories to CRSP securities. This is a reasonably high proportion and because the ratio for stocks and newsflow is comparable, it does not seem to discriminate small stocks. The quality of the matching is consistent over time and approximately equally high for agency and wire announcements (see Figure 2.4).

[Figure 2.4 about here]

The last transformation involves aggregating all stories released within the same trading day to match the daily frequency of stock returns. For this purpose I develop the following score, which basically weighs the tone of each story with the probability of its assignment and divides by the number of stories:

$$Tone = \frac{\sum 1 \cdot prob_{pos} + \sum(-1) \cdot prob_{neg}}{n_{pos} + n_{neut} + n_{neg}} \in [-1; 1] \tag{2.1}$$

Given that most of the results in the paper are for daily frequency, it is very important to avoid any kind of look-ahead bias. To best reflect the information set available to investors, news which arrived after the close of day t is shifted to the next trading day, thus Monday news includes stories from the weekend and similarly for trading days following public holidays.

For the sample selection, I apply the same filters as Tetlock (2010) and retain only company-days for which the most recent closing price was above $5 and the stock has traded on all of the preceding 60 days. After the screening there are 5'507'259 observations for 4'428 distinct stocks and 918'774 of them are news days. To take into account the importance of earnings announcements, I collect quarterly earnings dates from IBES and cross-check them with Compustat to make sure they are correctly identified. Subsequently, announcements which happened after market close (the majority in later years) are pushed to the following trading day and matched with general dataset. Earnings announcements account for 48'235 of the news days over the sample period.

2.3 Methodology

To study how news with different characteristics impact information asymmetry, I make use of the basic predictions of the stylized model of Tetlock (2010). I focus on the first three predictions, which can be examined using daily data.:

1. news reduces return reversals
2. high-turnover news reduces reversal even more
3. the correlation between absolute return and turnover is higher in the presence of news

The first two prediction are incorporated in a regression setup, where the excess return of firm i on day t is used to predict its excess return over the days $[t+2{:}t+10]$. The effect of news is modeled as an interaction term between day t excess return and a dummy variable equal to one if day t was a news day and zero otherwise. Contrary to Tetlock (2010), I do not demean the news dummy as to make the interpretation of the coefficient more straightforward. The regression also includes interactions between: day t excess return and abnormal turnover on day t; excess return, abnormal turnover and news (second prediction above) as well as news and abnormal turnover. The following control variables are also included: size, book-to-market ratio, abnormal turnover, past return and past volatility.

$$\begin{aligned} exret_{i,t+2:t+10} = \alpha_t + \beta_1 \cdot exret_{i,t} + \beta_2 \cdot news_{i,t} \cdot exret_{i,t} + \beta_3 \cdot news_{i,t} \cdot abturn_{i,t} + \\ + \beta_4 \cdot news_{i,t} \cdot abturn_{i,t} \cdot exret_{i,t} + controls_{i,t} + \epsilon_{i,t} \end{aligned} \tag{2.2}$$

The definitions of all variables follow standards widely accepted in the literature. Excess return is the company's raw return minus the CRSP value-weighted market return. For the ten-day horizon this is computed as the ratio of stock prices at the end and the beginning of the period minus the ratio of the respective value-weighted index levels, which is a more accurate measure than the sum of daily returns. Turnover is calculated as the ratio of daily shares volume and shares outstanding. To reduce the skewness of the turnover distribution I use logarithms and to avoid the problem of zero turnover I follow the method applied in Llorente, Michaely, Saar, and Wang (2002) and add a small positive constant[1] to each raw turnover value. Finally, abnormal turnover is the difference between log turnover on day t and the 60-day moving average of log turnover. Including abnormal turnover also as a control variable if motivated by the findings of Gervais, Kaniel, and Mingelgrin (2001). Size is the log of market capitalization at the end of the previous month. Book-to-market ratio is computed at the end of June each year, using the end-of-month market capitalization and book equity for the previous year, as in Fama and French (1993). Momentum is the raw return over the past 12 months, skipping the most recent month. Past volatility follows the definition of Ang, Hodrick, Xing, and Zhang (2006) being the standard deviation of daily returns over the past 21 days.

I estimate the coefficients using a single OLS regression with day fixed effects, to allow for a time-varying component of excess returns, and standard errors clustered by firm and day, which is the best way to control for two-dimensional correlation of residuals according to Petersen (2009). The within-firm correlation is to some extent hardwired into the regression because the dependent variable is measured over overlapping 9-day periods. There is likely to still be some within-day correlation, even after taking out market-wide shocks with the fixed effects, e.g. due to the co-movement of stocks from the same industry. Clustered standard errors are robust to arbitrary correlation structure within the clusters, and thus suitable for the task.

The results in Table 2.1 closely reproduce those of Tetlock (2010) in terms of the signs of the variables and their significance. The most important finding is that news significantly reduces reversal. To gauge the magnitude of this reduction, one can combine the coefficients on $Exret^{*}News$, $Exret^{*}Abturn$, $Exret^{*}News^{*}Abturn$ together with the average values of $Abturn$ on news and no-news days and compute the reversal for those two categories respectively. The proportion of day t excess return reversed over days $t+2$ till $t+10$, conditional on day t being a no-news day, is 4.2%, somewhat smaller than the 10.2% reported by Tetlock (2010). However, it is much closer to the $\sim 7\%$ he reports for the second part of his sample

[1]The magnitude of this constant, 0.00000255, is chosen as to make the distribution of turnover closer to normal, see e.g. Richardson, Sefcik, and Thompson (1986) for the argument

(1997-2007), which is more comparable to my sample period (2003-2011)[2]. By contrast, the reversal after news days amounts to 1.3% of day 0 excess return i.e. less than one third of what it is after no-news days. It is also true that news accompanied by high turnover have an even stronger effect on reversal. Reversal shrinks to just 80bp of day 0 return after high turnover news days, where high is defined as the 90th percentile of the turnover distribution for news days. Thus, as predicted by the model, turnover serves as a proxy to distinguish between informative and uninformative news stories. This interpretation is supported when earnings and non-earnings news are considered separately in the regression[3]. Earnings news are identified by matching news days to earnings announcement dates provided in IBES. The news in this group represent probably the most important of all company announcements. Consequently, they have a very large impact on reversals, in fact there is positive return autocorrelation after such news, consistent with the post-earnings drift literature, which does not further depend on turnover. By contrast, the impact of non-earnings news, which are much more heterogenous with respect to their importance, does significantly increase with turnover.

[Table 2.1 about here]

The results mostly hold in subsamples roughly corresponding to the period before and after the onset financial crisis. This is an important result, because not many standard asset pricing relationships hold during the crisis[4]. The effect of news appears to be smaller (though still significant at the 10% level) relative to no-news reversal during the crisis, suggesting that news was resolving less asymmetric information at that highly uncertain time. This is probably because there was a lot more confusion not just among investors but also news agencies. Accordingly, turnover is a much more significant proxy for informativeness during the financial crisis.

Other variables also return coefficients in line with expectations. The return-turnover interaction, $Exret^{*}Abturn$ is insignificant, much like in the second subsample of Tetlock (2010). The same applies to the return-size interaction. Among the usual control variables, size and momentum, are strongly affected by the financial crisis, which does not come as a surprise. Especially momentum changes from significantly positive to significantly negative after the beginning of the crisis. On the other hand, the value book-to-market and turnover effects appear robust in subsamples.

[2]The apparent decrease in the magnitude of daily reversal is also visible when comparing the pre- and post-2008 subsamples.

[3]Technically this involves replacing the single dummy for all news with two dummies, one for earnings and one for non-earnings news.

[4]For instance there is no size effect in the 2008-2011 subsample and the momentum effect actually switches signs.

Estimating the baseline specification with the Fama-Macbeth two-step procedure used originally in Tetlock (2010) leads to almost identical results. However, this approach, being based on averaging coefficients from daily cross-sectional regressions, has one serious limitation once news categories are introduced - there might be zero news items from a particular category on a given day. One could in that case treat this particular estimate as missing, resulting in time series of different length for different variables, or drop the entire day from the sample. Neither is a desirable outcome and it is only aggravated as the categories become more differentiated and the proportion of zero-news days grows. The single regression does not suffer from this problem and is therefore the preferred approach for the detailed analysis.

[Figure 2.5 about here]

The final prediction of the model states that the correlation between absolute return and trading volume increases when news is released. Empirically, I construct event time plots of the correlation between absolute excess return and log abnormal turnover across all news events on the event day (day 0) itself as well as up to ten days before and after. In Figure 2.5 the spike at 0 is very prominent, while the control group for which day 0 is chosen to be a no-news day shows no such clear pattern over the event window. The apparent slight drop in correlation on day 0 is most likely due to the fact that for the control group day 0 is by definition a no-news day, while any other day in the event window can be either a news or no-news day. The magnitude of the increase in correlation should be proportional to the informativeness of the news, so in the detailed analysis I construct similar plots for all the news categories for which I estimate the OLS regression.

To relate the role of news to the characteristics of companies an their information environment, I estimate the baseline regression in Eq. 2.2 separately in subsamples of stocks sorted on size, book-to-market, past return, analyst coverage, analyst dispersion and institutional ownership. The first three characteristics have already been used as control variables in the original estimation but the idea here is to examine their interaction effects with news. The latter three characteristics are intended to capture availability, consistency and ability to process information respectively. Especially the role of institutional shareholders as proxy for informed traders seems especially relevant in light of the structure of the theoretical model. The ranking are updated every quarter (at the end of June each year for book-to-market) and tercile breakpoints are used. Given that all other characteristics correlate positively with size, those rankings are size-adjusted by first computing tercile breakpoints for a given characteristic in each size tercile and then pooling observations together across size terciles. Thus, the bottom tercile of e.g. institutional ownership will contain the one third of stocks with the lowest fraction of institutional holdings from all size terciles.

Results for the individual subsamples suggest that the resolution of asymmetric information through public news does not depend on the availability or consistency of analyst coverage (Panels D and E of Table 2.3). On the other hand, the impact of news on reversal varies significantly with size, past return and institutional ownership (Panels A, C and F). It appears reasonable that the effect of news is insignificant among stocks with little institutional shareholders for which the main mechanism of resolving information asymmetry through public news - passing information from informed traders to the uniformed - is likely to be weaker due to the scarcity of informed traders overall. For stocks with a medium and high share of institutional owners, the effect is highly significant. The rankings on size and past return offer interesting hints as to which types of news are likely to play a larger role in resolving asymmetric information. On one hand, the fact that in the group of stocks with highest past returns there is no significant effect suggests that positive news is less informative than negative news, because past winners also have the most positive coverage. On the other hand, the insignificance of the estimates among largest stocks points to the source of the news as an important factor. This is because small and big stocks have quite a different structure of newsflow, with a much higher share of agency-originated news in the latter group. Liquidity is less likely to be an issue, since the effects of news is actually stronger among more liquid stocks. Thus, both source and tone seem important for the role of news in resolving asymmetric information and will be examined directly in the next section.

2.4 News source, news tone and asymmetric information

Given that news is found to resolve asymmetric information, it is natural to ask whether all news is equal in this respect or whether there are differences. In essence, the question is about the informativeness of different types of news. Tetlock (2010) considers the number of individual news items per story for this purpose, while Tetlock (2011) focuses on the news staleness. Neither of them however differentiates between positive and negative tone nor the source of the news, although these distinctions seem to be at the core of the different factors and incentives shaping the role of financial news.

On one hand, news originated by the companies themselves and usually disseminated through channels like the PR Newswire and Business Wire has the most potential to contain genuinely new information, because companies are best informed about their own business. However, they also have incentives to present themselves favorably. On one hand, the "materiality" threshold companies have for releasing positive news is likely to be much lower than for negative news. This is the case of endogenous disclosure modeled by Acharya, DeMarzo, and Kremer (2011). On the other hand, even when forced to disclose bad news, companies might be inclined to relativize the negative content by focusing e.g. on ways to overcome currently experienced difficulties, rather than the difficulties themselves. The tendency to publicize every positive development coupled with watering down bad announcements could act to reduce the average informativeness of company-originated news, especially good news.

The other important actors in the business of financial reporting are the news agencies like Reuters or Bloomberg, whose reputation is built on delivering timely and accurate information to millions of investors worldwide. In practice they face a delicate balancing act. On one hand, merely passing on company-originated announcements would not justify the expensive subscriptions paid by the clients, so the agencies are expected to excel at picking the most important news. Ideally, they would also conduct independent critical investigations but this is often impossible without information that only the companies themselves can provide. As a result, news agencies necessarily rely on good relationships with companies but companies might be reluctant to provide information if it was to be used for negative coverage. Thus, there could also be a tendency towards positive coverage. In fact, Solomon (2012) shows that investor relations firms hired by some companies can successfully increase the number of articles in the financial press following positive corporate announcements.

To investigate these two dimensions, I first categorize all news days into positive, neutral and negative in a manner similar to Tetlock, Saar-Tsechansky, and Macskassy (2008). Specifically, a news day is deemed positive (negative) if the weighted average news tone on that day falls in the upper (lower) quartile of the previous quarter's distribution and it is deemed neutral if falls in between the quartiles. This procedure leads to the loss of one calendar quarter of data but takes into account secular trends in the overall tone, which are expected to be quite pronounced given that the stock market went from a very strong bull to a very deep bear market in this period. Figure 2.6 plots the quarterly breakpoints, showing considerable variation in the lower breakpoint, which drops from a high of 0 in 2006 and 2007 to a low of -0.34 in early 2009. Interestingly, the upper breakpoint undergoes much smaller swings, indicating that at least part of the newsflow was remarkably and consistently positive even during the financial crisis. Figure 2.6 also confirms that the bias in the distribution of individual news stories carries over to the distribution of news days. The fact that the lower quartile is just slightly below zero most of the time means that days with basically neutral stories were already among the worst 25% by tone.

[Figure 2.6 about here]

Separately, I label news days as 'wire' if they contain only news that was originally published on PR Newswire, Business Wire or one of similar direct corporate channels or as 'agency' if the news came from one of the Reuters feeds. For news days there is also the third possibility that both types of news can also appear over the course of the same day. In this case I tend to assume that company and agency news are contentwise related.

To test for differences with respect to news tone, I first estimate the regression in Eq. 2.2 replacing the news dummy with three dummies for positive, neutral and negative news days respectively. The upper left section of Table 2.4 reports the key coefficients describing the relationship between tone and information asymmetry. The insignificant coefficient on $Exret^{*}News$ for positive news reveals that on average it does not reduce return reversals, suggesting it contributes little to resolving asymmetric information. On the other hand, the coefficients for neutral and especially negative news are both positive and significant. The significance of the coefficients on $Exret^{*}News^{*}Abturn$ appear complementary to $Exret^{*}News$, underscoring the importance of turnover as a proxy for informativeness when the average piece of news is not very informative, as is apparently the case with positive news. These conclusions are supported by examining the absolute return-turnover correlations in Figure 2.7. There is still a moderate increase in correlation for positive news days, indicating that at least some of them are indeed informative. Negative and neutral news both have a much bigger impact and there are no further significant differences between these two groups.

[Table 2.4 about here]

Similar differences emerge when categorizing news by source. Looking at the upper right section of Table 2.4, the insignificant coefficients on $Exret^{*}News$ for agency and wire news days suggest that neither resolves asymmetric information when released on its own. However, when both are combined, the impact on return reversal is significant. In fact, there is no reversal at all after news days with stories from both sources. This finding sheds some light on the role of news agencies in financial markets, which appears to be primarily identifying important company announcements rather than generating their own stories. The fact that the coefficient on the triple interaction term for agency and wire news days is significant and positive, while being insignificant for the 'both' group supports this view. To the extent that high turnover helps distinguish between informative and uninformative news, agency coverage of a corporate announcement seems to have the same effect. The correlation plots in Figure 2.7 offer an additional insight into why agency stories, which are not accompanied by wire news, might be uninformative - the market appears to move ahead of them. The spike in absolute return-turnover correlation happens already one day before a typical agency-only news day. It is true that the decline in correlation following the spike is slowed down by the occurrence of agency-only news but the overall impact is below that on days featuring news both from companies and agencies. One interpretation would be that in the absence of new company events, the news agencies tend to report about stock market movements, thus creating the apparent lag.

[Figure 2.7 about here]

Given the evidence on the positive skew in wire news, it is compelling to ask whether the effects discussed in the previous two paragraphs are in fact overlapping, that is whether the lack of significance documented for wire news is due to them for the large part positive and *vice versa*. To this end I sort all news days first by tone category and within each of those categories by the source of the news. The results in Panel B of Table 2.4 show that these are distinct effects. Although it is true that positive wire news does not resolve asymmetric information when released alone, the same applies when it is neutral or negative. Conversely, the combination of agency and wire news does seem to resolve asymmetric information only when it is overall neutral or negative. This finding is supported by the correlation analysis as well. Though the absolute return-turnover correlation does feature a spike on day 0 for positive news days in the 'both' category, the spike is much smaller compared to the neutral and negative cases. This raises the question whether the role of news agencies is not only in identifying important corporate announcements but also "toning them down" and filtering out the excessively positive content or making more clear the negative aspects of the original release.

To answer it one could look at the tone of individual *stories* released on the wire and by agencies, if both appeared on the same day. Looking at the right hand side of Panel C in Table 2.4 confirms that agency stories are substantially less positive than contemporaneous stories on direct wires. There is no such difference if wire and agency stories are released alone, suggesting that this is not due to a secular difference in language used by companies and agencies. However, it is important to observe that this "toning down" effect of agency news works only if the wire news itself was somewhat negative or at least neutral. For clearly positive wire news, agency news tends to follow suit thus leading to the whole news day also being categorized as positive. It is remarkable that this is also the only case where combined wire and agency news do not contribute to resolving asymmetric information. Two possible mechanism could explain this finding. It could either be that for these clearly positive wire news the agencies are subject to spin or they tend to simply relay the original company announcement. Evidence of the first mechanism was presented by Solomon (2012) but there is also evidence in support of the second one, as will be shown in subsection 2.4.2. Either way, news agencies in the face of positive wire news appear to give up on one of the important roles they play in news dissemination, which is challenging the overly optimistic tone of company news and by that making it more informative for investors.

2.4.1 Other news characteristics affecting asymmetric information

The purpose of this section is to investigate what other characteristics matter for how news influences asymmetric information. The question is essentially about identifying more informative news through factors other than newsday turnover. Thus, a particular news characteristic should first of all significantly affect news-return reversal relationship (to be able to say it has an impact on the resolution of asymmetric information), and ideally also decrease the triple news-return-turnover interaction (so that it partly takes over the role of turnover in identifying informative news).

The first characteristic under consideration is the number of individual news items released during day t (*count*), which relates to the practice of news agencies to publish stories in parts. Tetlock (2010) has suggested that the number of news items proxies for the thoroughness of the story made up from them. One reason for this could be that more parts increase the overall length of the story and longer stories have greater potential to be informative. An alternative channel would be that having more parts usually also means a story is spread out over a larger portion of the day and can thus include updates on subsequent developments, compared to a story released at a single point in time. To distinguish between these two channels and also directly test whether longer stories are more informative, I include the total length (number of words, *words*) in a story as a characteristic. In case there were several stories on a given day, I take their average length. Finally, one could consider how much a story is focused on a particular company. This can be approximated by counting words in the text relating to that company (e.g. by appearing in the same sentence as the company name or ticker) and taking the ratio of these "relevant" words to total words ($fraction$). One would intuitively expect more focused news to be able to deliver more information about the company and thus resolve more of the information asymmetry.

Methodologically, I first demean each characteristic by day and size quintile (this is especially important for *count*, which is positively correlated with size) and add them to the regression equation by interacting them with the $Exret^{*}News$ variable. I take the natural logarithm of the number of words before demeaning to reduce the large skewness of this variable. Due to the demeaning, the coefficient on $Exret^{*}News$ has the interpretation of the effect on reversal of news with the average value on each characteristic. The coefficients on $Exret^{*}News^{*}[characteristic]$ on the other hand, give the effect of a unit increase in either *count*, *words* or $fraction$.

[Table 2.5 around here]

In terms of summary statistics, Panel A of Table 2.5 presents the standard deviations (means are zero by construction) and correlations between the three characteristics. Two effects that stand out are the virtual lack of correlation between *count* and *words*, indicating that stories consisting of more parts are not necessarily longer, and the strong negative correlation between *words* and $fraction$. The consequences of this negative correlation are apparent in the regression estimates in Panel B. There, the log of the number of words per story has the expected positive sign, meaning that longer stories do indeed convey more information. On the other hand, the fraction of words related to the company is significantly negative. When both are included in the regression, only the former remains significant, so lower fraction is just proxying for greater story length. Increasing the number of individual news items also does have the predicted effect of reducing reversal but the effect is concentrated at the low end of the range. Beyond a certain threshold, additional news items do not seem to have an additional impact. Finally, including all three variables in the regression shows that the number of news items and the number of words are in fact distinct channels increasing (for *count* up to a certain point) the informativeness of news stories. This hints at the "spreading out" effect of *count* though it would be interesting to provide direct evidence of this interpretation. It should also be noted that the news-return-turnover interaction remains significant in all regressions, also in the full specification in the rightmost column, so the list of important news characteristics, to which the market reacts, extends beyond the ones discussed here.

2.4.2 Relation of other news characteristics to news tone and news source

An additional question concerns the way in which other news characteristics might be connected to news tone and news source examined earlier. In particular, can they be helpful in explaining why only news days with both wire and agency news contribute to the resolution of asymmetric information and only if the resulting combination is not positive? Comparing the left and right half of Table 2.6, it is indeed the case that the count of individual news items is higher on days with news from both companies and agencies, than on days with only one type of news, an effect which is expected to arise almost mechanically. However, the average length of a news story is also greater on days with both types of news, which is less obvious and suggestive of longer wire news being more important, if they are more likely to be picked up by news agencies. In terms of news source and the fraction of words related to the company, there are two pattern to be seen. On one hand, agency news released on its own is less related to a particular company than agency news released on the same day as wire news. This is intuitive evidence of the fact that when news agencies release on a day with wire news, they are indeed inspired by the content of the company announcement. The other pattern is more intriguing. Although agency news generally has a lower or very similar fraction compared to wire news, there is one notable exception - for negative news days featuring both types of news, the agency news has a significantly higher fraction of words related to the company. This is mostly due to the fact that the fraction of related words for corresponding wire news is unusually low - just 55% of words are deemed relevant.

[Table 2.6 around here]

The fact that negative wire news generally has a lower fraction of words related to the announcing company (it is also true of wire news released on its own) brings the attribution bias to mind. This bias is very well-known in psychology and has also found extensive application to finance, see Gervais and Odean (2001) or Coval and Shumway (2005) for empirical evidence and Daniel, Hirshleifer, and Subrahmanyam (1998) for a theoretical representation. It basically describes the human tendency to ascribe successes to own actions (internal factors) and explain failures through adverse circumstances (external or situational factors). Translated onto financial news, this would manifest itself in very prominent portrayal of the company in positive news and playing down its role in negative news while concentrating on e.g. the general market environment, something that Clatworthy and Jones (2006) have documented for CEO letters to shareholders. Of course, at the level of the company it might well be a deliberate PR strategy rather than an unconscious bias but the underlying mechanism is the same. The desire of companies to "explain" their negative news through outside effects is also apparent in negative wire news being substantially longer than positive.

Agency news in this context seems to play a useful role in the sense of staying focused on the company itself, a likely consequence of the fact that agency news is generally much shorter than wire news and especially so if both are issued on the same day. This also seems to explain why in the case of an overall negative or neutral combination of wire and agency news, the latter was much more negative in tone (see bottom panel of Table 2.4). The mechanism behind what was called "toning down" appears to be in fact "shortening down". For negative news this also apparently has the effect of making the negative message more direct - by eliminating the layer aimed at explaining bad company news through external factors - and thus more informative. The fact that news agencies do not make positive wire news more informative is also consistent with this mechanism. There, the underlying company-related content is anyway positive (and also much more concise), so a summarized version of the company announcement supplied by the news agencies does not add much to the overall news informativeness.

2.5 Conclusions

To answer the question of which news resolves asymmetric information, more than 1mln company-specific news stories were analyzed over the period 2003-2011. Departing from the empirical hypotheses provided by the stylized model of Tetlock (2010), the study focuses on two dimensions of public news: its source and its tone. On any given news day, the source of the news can be either the companies themselves, news agencies such as Reuters, or both. Tone differentiates news based on whether from a linguistic point of view it conveys positive, negative or neutral content.

Three empirical effects should be observed if news resolves asymmetric information: short-term return reversal should be smaller after news days compared to no-news days, news days accompanied by high turnover should reduce reversal even more and, the correlation between absolute return and turnover should be higher on news days. Together they are representative of a market in which signals about future payoffs are initially held only by a privileged group of informed investors, who however suffer from a liquidity shock, and are subsequently revealed through public news. The remaining investors, having seen the news, are also able to infer the size and direction of informed traders' liquidity shock and are more willing to accommodate it, generating the patterns described above. One can see that the critical parameter in this setup is the informativeness of public news.

I find that all three effects apply to news issued over my sample period. Importantly, they do not disappear during the financial crisis, underscoring the continuous importance of public news to financial markets. Additionally, the effects are not limited to earnings announcements, which are clearly informative and have been comprehensively studied in the literature, but extend to other news as well.

Differentiating news by its source reveals that neither direct wire news from the companies, nor agency news from the likes of Reuters contributes to resolving asymmetric information when issued in isolation. Only news days featuring a combination of news from both sources are associated with subsequent reversals, which are significantly lower on average. Thus, it seems that news agencies are effective in selecting the most interesting corporate news to report on, which is arguably one of the most important reasons for their existence. They are, however, apparently less successful in generating interesting news of their own accord. In particular, analyzing absolute return-turnover correlations around pure agency news reveals that the spike predicted by theory occurs one day before the news and already begins to decrease, albeit slowly, on the day the news released, suggesting the market reacts ahead of such stories.

A related finding is that the average piece of positive news also does not resolve asymmetric information. Intuitively, this could be interrelated with the insignificance of wire news, because such news tends to be positively biased for rather well-known reasons. As it happens, these are two distinct effects as evidenced by the fact that wire news remains insignificant even if negative and conversely, positive news remains insignificant even when it comes from both sources on the same day. By contrast, reversals after negative and neutral news days with stories from both sources are significantly smaller. A closer look at this phenomenon points to the second important role news agencies play in financial markets. Besides selecting important corporate announcements to report on, they also "tone down" those announcements, which is evident from the fact that a typical agency story has a more negative tone than a wire story issued about the same company on the same day. This content filtering apparently increases the informativeness of news for investors and it is therefore remarkable that it does not work for clearly positive wire stories. The explanation offered in this paper relates to the popular attribution bias, or a deliberate application of it by companies having to announce negative news. Such news tends to be much longer and less related to the company compared to positive, indicating that external circumstances are being called upon by companies in order to "explain" the negative news and make the company itself look less bad. Agency news by contrast are much shorter and stay focused on the company itself, thus making the negative message more direct. Such shortening however, cannot work when the original content of wire news is already positive, consistent with the empirical findings. This mechanism could work parallel to or reinforce the effects of spin documented elsewhere in the literature. Taken together, this lack of filtering of positive wire stories seems to explain, why adding agency coverage does not make them more informative.

An additional finding relates to the role of turnover as a proxy for news informativeness. In short, high turnover significantly increases the impact of news categories, which are insignificant on average, such as positive or wire news. This suggests that at least some news stories in these categories are indeed informative and it is a compelling direction for future research to search for more direct measures of news informativeness, besides tone and source. Three such characteristics, the count of individual news items, the number of words in the story and the fraction of words relating to the company have been tested and the first two found to be significant. However, none of them nor their combination drives out the turnover effect, suggesting the list of important news characteristics is longer and inviting further research.

Finally, the model in the form laid out in Tetlock (2010) makes several assumptions about how investors interact with news. First of all, it assumes that investors take notice whenever a piece of public news arrives. Given the ever increasing news volume and evidence of limited or selective attention, this does not need to be true. Furthermore, it assumes that once investors have read the news they fully to understand it and optimally retrieve the signal it conveys about future payoffs. Whether they are indeed able to do that in the complex world of financial markets is also open to question. Relaxing either assumption would also be interesting for further research.

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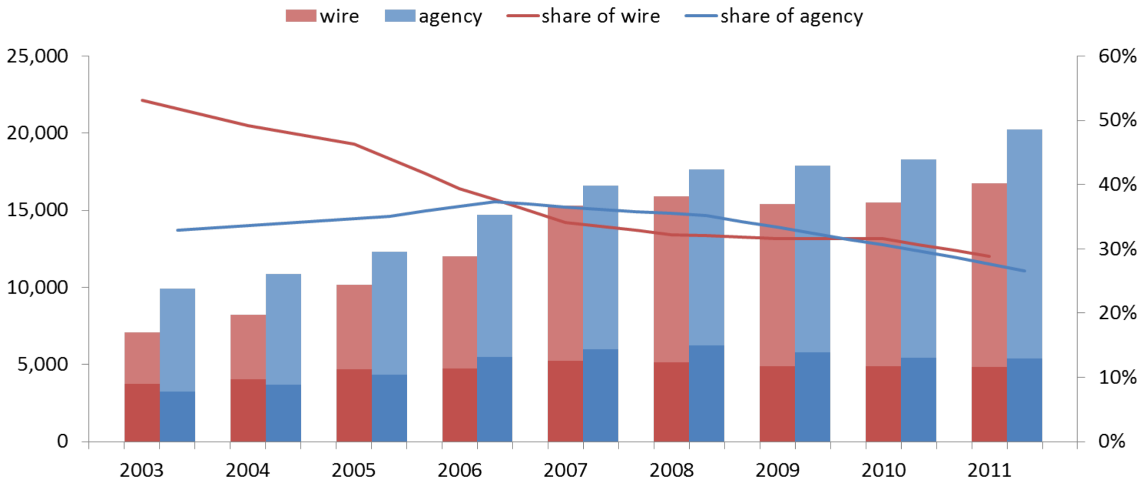
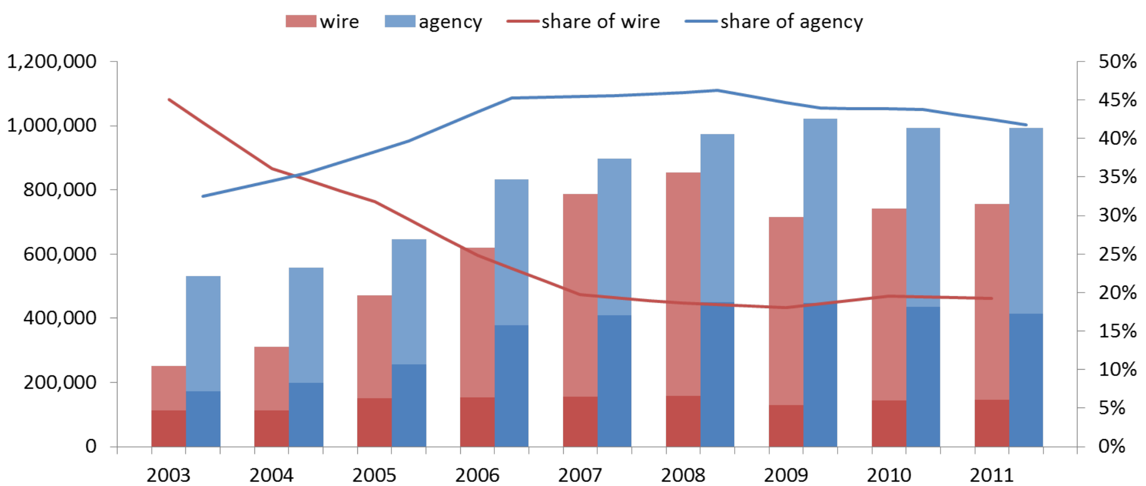
Figure 2.1: US share of global newsflow

(a) Distinct stocks



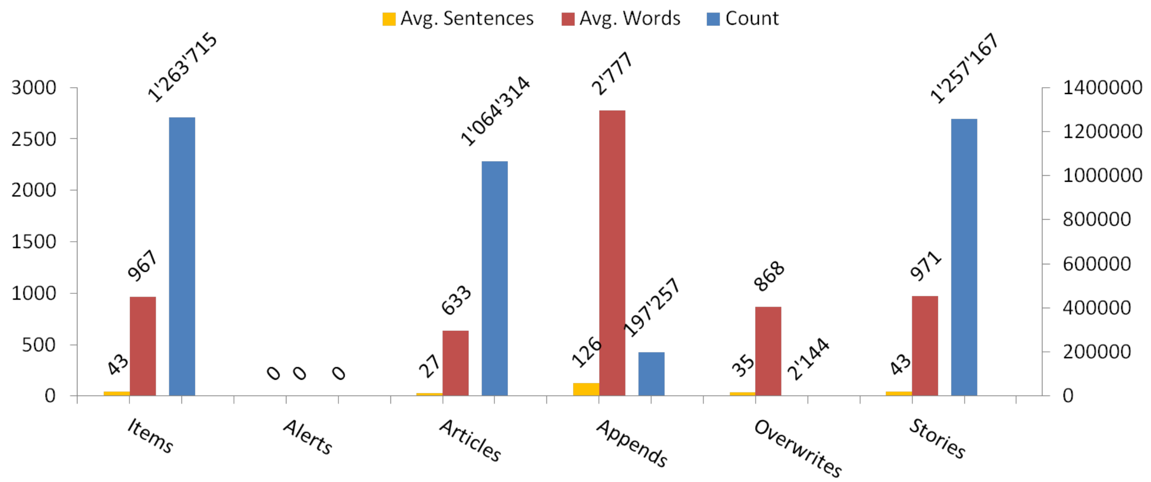
(b) News items



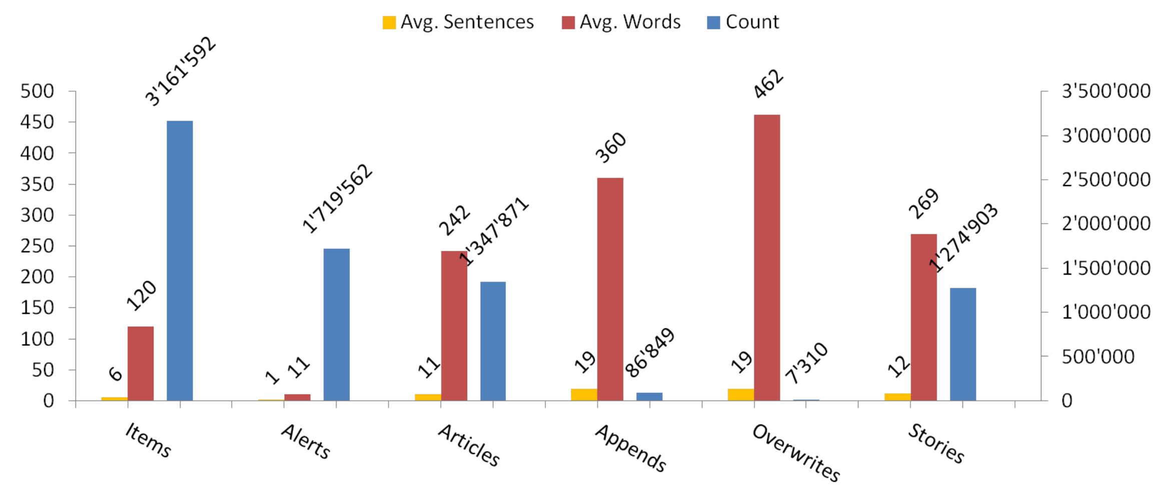
The columns in Panel (a) represent the number (on the left axis) of distinct stocks linked to wire (red columns) and agency news (blue columns). The full column gives the global number, while the solid part represents the US. The red and blue lines give the US share (right axis) of global stocks linked to wire and agency news respectively. Panel (b) performs the same analysis for individual news items.

Figure 2.2: Distribution of news items by type

(a) Wire news



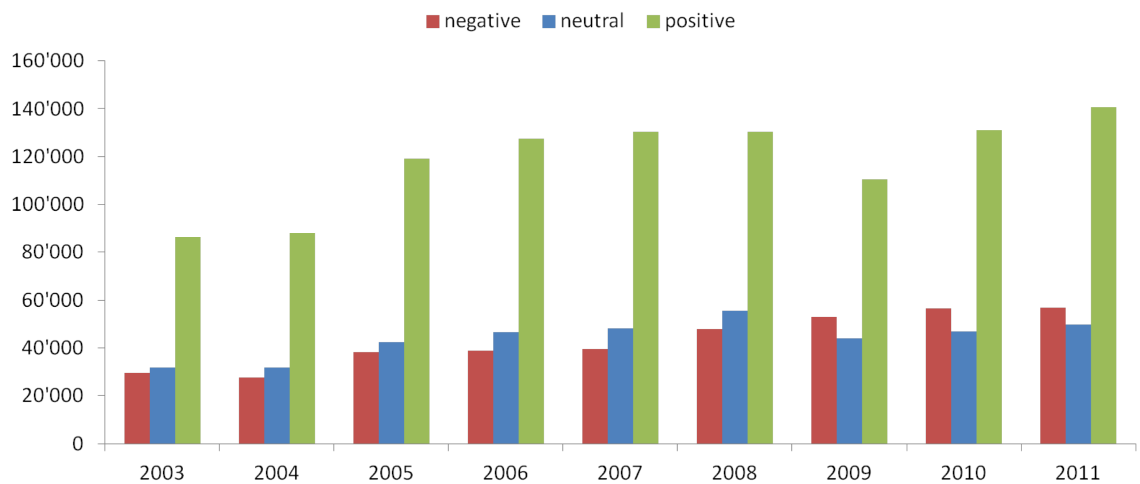
(b) Agency news



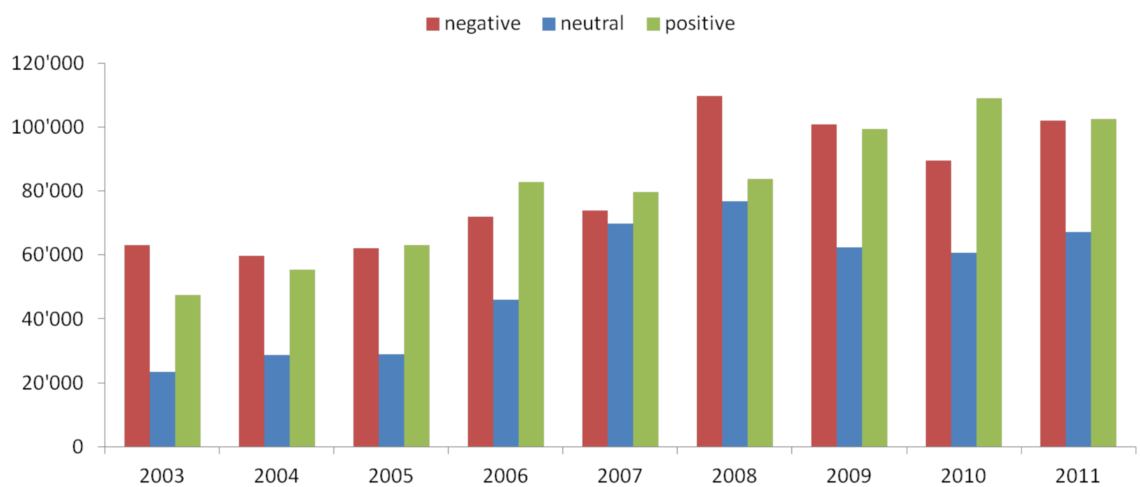
The plots show the total number (right axis) as well as the average number of words and sentences (left axis) for all individual news items, news item grouped by the four distinct categories as well as per story basis. Stories are identified as all news items sharing a common PNAC (Primary News Access Code) identifier. Because PNACs can be reassigned after a certain time, a news item has to appear within 14 days since the last item with the same PNAC to be treated as part of the same story. The statistics are computed for agency and wire news separately.

Figure 2.3: Distribution of stories by tone

(a) Wire news



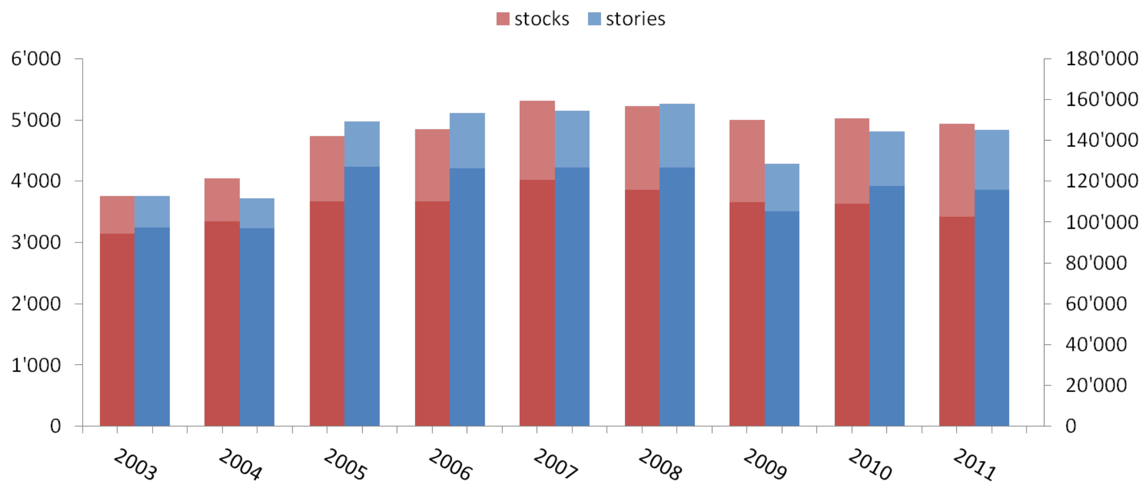
(b) Agency news



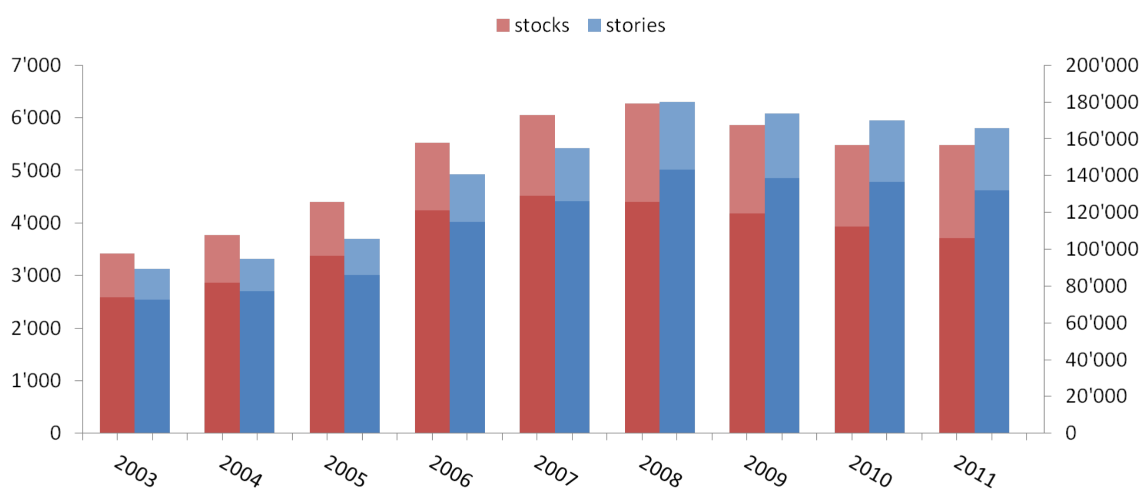
The plots show the total number of stories broken down according to their tone. The three tone categories are 'negative', 'positive' and 'neutral', with the latter meaning neither a negative nor a positive assignment could be made. The assignments are determined by a language processing algorithm, which scans the text and searches for similarities to stories evaluated by humans. The numbers are computed for agency and wire news separately.

Figure 2.4: Matching RICs to PERMNOs

(a) Wire news



(b) Agency news



The plots show the effectiveness of matching individual stocks (left axis) and the corresponding news volumes (on a per story basis, right axis)) from the Thomson Reuters News Analytics database to CRSP. For each column, the solid part represents the fraction of stocks or stories that could be matched in a given year. The numbers are computed for agency and wire news separately.

Figure 2.5: The impact of news on the correlation between absolute returns and turnover

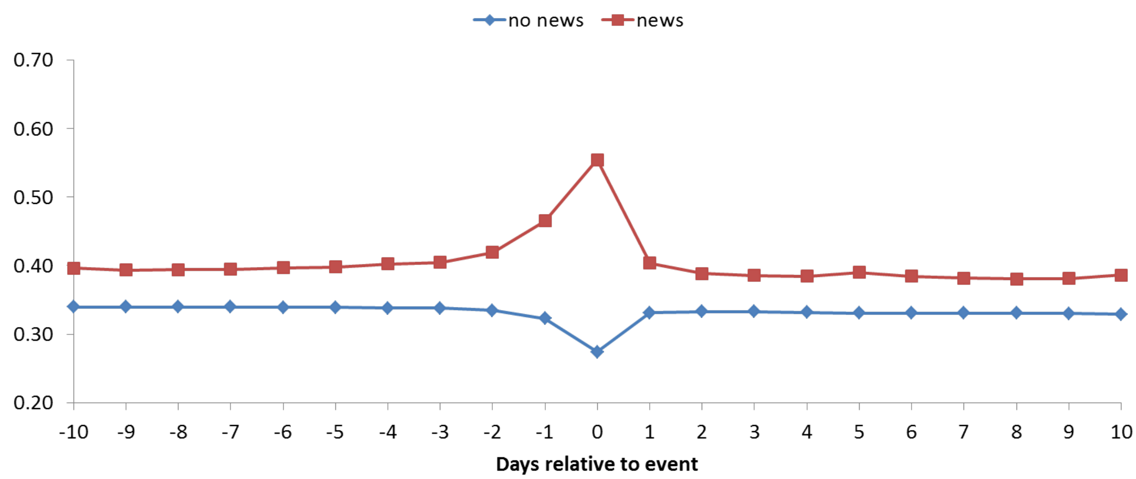
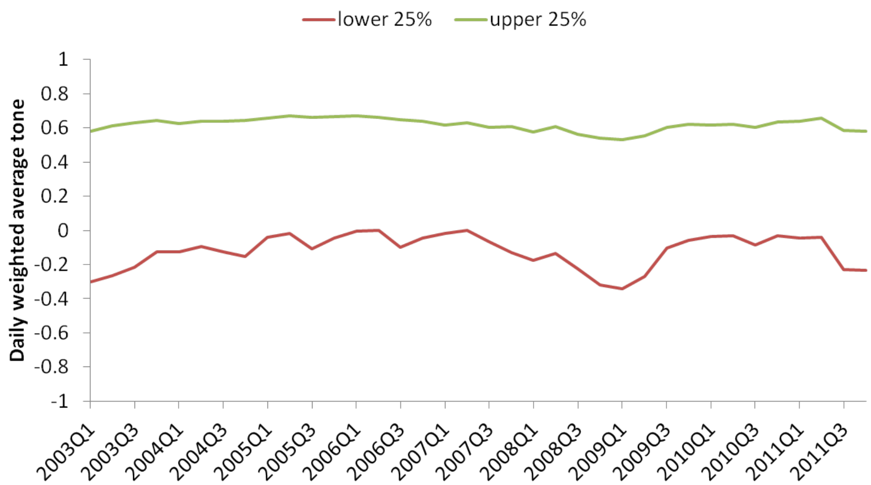


Figure 2.5 shows daily cross-sectional correlation between abnormal return and turnover plotted in event time. An event is defined as either a news day or a no-news day. Each daily correlation is computed using all observations from all stocks, which are either on the event day or the respective number of days away from it.

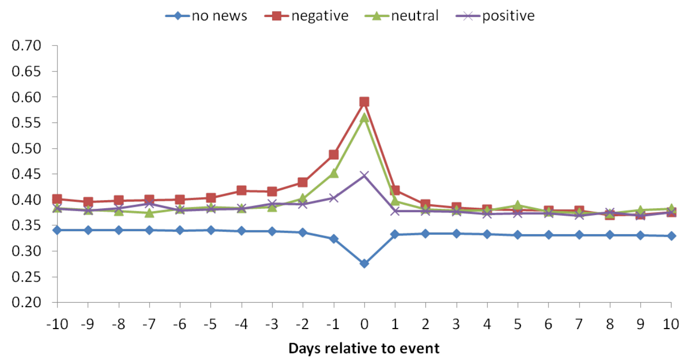
Figure 2.6: Positive and negative tone breakpoints over time



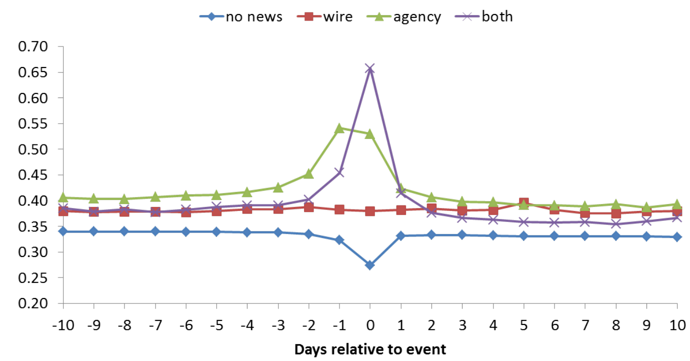
Plotted above is the time series of the breakpoints used each quarter to differentiate between positive, neutral and negative news days. Positive news days are defined as falling into the top 25% of the previous quarter distribution of weighted average tone (above the green line) and negative ones as falling into the bottom 25% (below the red line). News days in between the two lines are classified as neutral.

Figure 2.7: The impact of news tone and source on the absolute return-turnover correlation

(a) by tone

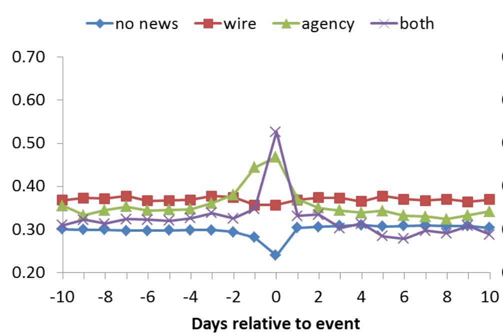


(b) by news source

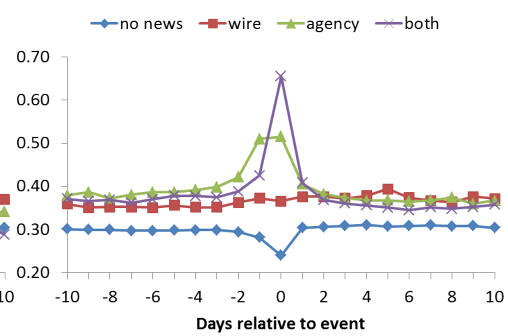


Sorting first by news tone and then by source

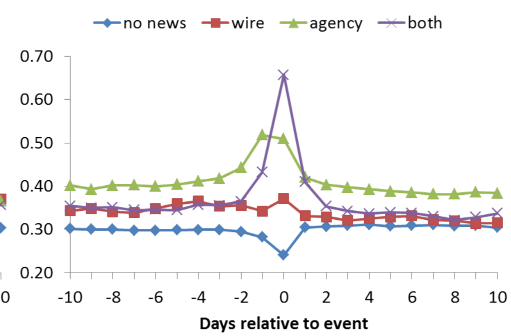
(c) positive



(d) neutral



(e) negative



In Figure 2.7 the impact of news on the correlation between absolute returns and turnover is described in more detail. Daily cross-sectional correlation between abnormal return and turnover are plotted in event time, where an event is defined as either a news day or a no-news day. Each daily correlation is computed using all observations from all stocks, which are either on the event day or the respective number of days away from it.

The upper two plots categorize news days by news source and news tone respectively. The news source can be either 'wire', if the news on that day appeared on one of the direct corporate feeds such as PR Newswire and BusinessWire, or 'agency' if it was issued by the news agency. It can also be 'both' if news from both sources occurred on the same day. The news tone assignment is based on analyzing all news stories from a given day in a fashion laid out is Section 2. The lower three plots present return-turnover correlation in subgroups formed by sorting first on news tone and then on news source within each news tone group. The no-news event-time correlations are included in each plot for comparison.

Table 2.1: Baseline results on news and reversals

The Table presents results of estimating Equation 2 in the full sample and two subsamples divided by the beginning of the financial crisis. The estimates are obtained from a single panel regression using all eligible observations and including month fixed effects. The dependent variable is stock's i excess return over days $[t+2:t+10]$, which is regressed day t excess return $Exret$, the news indicator $News$, abnormal turnover $Abturn$ and two-way and three-way interactions between these variables. Furthermore the regression includes standard control variables such as $Size$, book-to-market ratio BtM, past returns Mom and past volatility $Pastvol$ as well as the interaction between size and excess return. To assess the role of earnings announcements in driving the overall results, in the three columns in the right the news dummy is replaced with two dummies for earnings and non-earnings news respectively. t-statistics appearing below the coefficients are computed from standard errors clustered on firm and day.
Significance levels: * - 5%, ** - 1%

	All news			Earnings and non-earnings news		
Variable	2003 - 2011	2003 - 2007	2008 - 2011	2003 - 2011	2003 - 2007	2008 - 2011
$Intercept$	0.0025	-0.0090 **	0.0012	0.0025	-0.0089 **	0.0013
	(1.37)	(-2.81)	(0.54)	(1.39)	(-2.80)	(0.56)
$Exret$	-0.0417 **	-0.0485 **	-0.0360 *	-0.0417 **	-0.0482 **	-0.0362 *
	(-3.86)	(-4.96)	(-2.02)	(-3.85)	(-4.92)	(-2.03)
$Exret * News$	0.0276 **	0.0391 **	0.0193			
	(3.82)	(4.56)	(1.74)			
$Exret * Earn$				0.0662 **	0.0566 **	0.0748 **
				(4.15)	(3.23)	(3.04)
$Exret * Nonearn$				0.0202 **	0.0328 **	0.0112
				(2.78)	(3.71)	(1.02)
$Exret * Abturn$	-0.0039	0.0036	-0.0136	-0.0044	0.0026	-0.0132
	(-0.72)	(0.68)	(-1.44)	(-0.81)	(0.48)	(-1.39)
$Exret * News * Abturn$	0.0103 *	0.0045	0.0173 *			
	(2.06)	(0.75)	(2.05)			
$Exret * Earn * Abturn$				0.0072	0.0109	0.0053
				(0.84)	(1.09)	(0.38)
$Exret * Nonearn * Abturn$				0.0108 *	0.0050	0.0173 *
				(2.13)	(0.81)	(2.04)
$Exret * Size$	-0.0040	-0.0031	-0.0046	-0.0035	-0.0026	-0.0041
	(-1.55)	(-1.28)	(-1.11)	(-1.39)	(-1.10)	(-1.01)
$News$	-0.0003 **	0.0000	-0.0007 **			
	(-2.45)	(0.17)	(-3.68)			
$Earn$				-0.0013 **	-0.0007	-0.0021 **
				(-3.04)	(-1.43)	(-2.75)
$Nonearn$				-0.0003 *	0.0001	-0.0007 **
				(-2.05)	(0.36)	(-3.33)
$News * Abturn$	-0.0006 **	-0.0012 **	0.0004			
	(-3.17)	(-5.54)	(1.23)			
$Earn * Abturn$				-0.0001	-0.0006	0.0008
				(-0.14)	(-1.40)	(1.09)
$Nonearn * Abturn$				-0.0006 **	-0.0012 **	0.0004
				(-3.18)	(-5.69)	(1.32)
$Abturn$	0.0017 **	0.0020 **	0.0011 **	0.0017 **	0.0020 **	0.0011 **
	(11.15)	(11.85)	(3.82)	(11.19)	(11.90)	(3.84)
$Size$	-0.0001	-0.0002 **	0.0001	-0.0001	-0.0002 **	0.0001
	(-1.05)	(-2.83)	(1.00)	(-1.11)	(-2.87)	(0.96)
BtM	0.0009 **	0.0012 **	0.0008 **	0.0009 **	0.0012 **	0.0008 **
	(5.42)	(6.34)	(3.49)	(5.41)	(6.33)	(3.48)
Mom	0.0000	0.0006 *	-0.0007 **	0.0000	0.0006 *	-0.0007 **
	(-0.04)	(2.28)	(-2.66)	(-0.04)	(2.28)	(-2.66)
$Pastvol$	-0.0196	-0.0214	-0.0230	-0.0197	-0.0214	-0.0232
	(-1.06)	(-1.21)	(-0.78)	(-1.06)	(-1.21)	(-0.78)
Number Of Observations	5'456'013	3'159'467	2'296'546	5'456'013	3'159'467	2'296'546
R-Squared	0.0198	0.0184	0.0212	0.0198	0.0184	0.0213

Table 2.2: Summary of company characteristics

For the purposes of this Table all company characteristics are measured quarterly (at the end of every June for BtM) and their definitions are as follows:

- Size, is the average market capitalization
- BtM, Book-to-Market, is the ratio of book equity reported for year t to market capitalization at the end of year t
- PastRet, is the cumulative raw return over the previous 12 months, skipping the most recent month
- AnCov, analyst coverage, is the number of analysts issuing forecasts before the most recent earnings announcement
- AnDisp, analyst dispersion, is the standard deviation of all forecasts before the most recent earnings announcement around the mean forecast
- InstOwn, institutional ownership, is the fraction of institutional shareholders
- Illiq, is the Amihud illiquidity ratio, computed as the average daily ratio of absolute return to dollar trading volume multiplied by 10^6

Means, standard deviations and correlations between all characteristics are reported in upper half of the Table. The lower half presents the breakdown of newsflow for companies sorted on past return (by news tone) and size (by news source).

	Size	BtM	PastRet	AnCov	AnDisp	InstOwn	Illiq
mean	6.83	0.63	0.23	6.31	0.04	0.64	0.05
std. dev.	1.64	0.60	0.85	5.59	0.17	0.28	0.20
Size	1	-0.181	-0.030	0.572	0.022	0.383	-0.345
BtM		1	0.171	-0.089	0.078	-0.079	0.118
PastRet			1	-0.055	-0.020	-0.150	-0.003
AnCov				1	0.029	0.255	-0.148
AnDisp					1	0.028	-0.003
InstOwn						1	-0.294
Illiq							1

share of all news days	by past return tercile		
	low	medium	high
negative	0.237	0.254	0.259
neutral	0.498	0.522	0.525
positive	0.265	0.223	0.217
	by size tercile		
	small	medium	big
agency	0.098	0.167	0.358
wire	0.670	0.607	0.365
both	0.232	0.226	0.277

Table 2.3: News and reversals in subsamples

This Table contains the results of the baseline regression for stocks grouped according to various characteristics. All rankings (except book-to-market) are updated quarterly and tercile breakpoints are used. Subsamples are generated by interacting all variables with a set of three dummy variables representing rank assignments, so that only one regression has to be estimated per ranking. The dependent variable is stock's i excess return over days $[t+2:t+10]$, which is regressed day t excess return $Exret$, the news indicator $News$, abnormal turnover $Abturn$ and two-way and three-way interactions between these variables. Furthermore the regression includes standard control variables such as $Size$, book-to-market ratio BtM, past returns Mom and past volatility $Pastvol$ as well as the interaction between size and excess return. t-statistics appearing below the coefficients are computed from standard errors clustered on firm and day.
Significance levels: ˆ - 10%, * - 5%, ** - 1%

	low		medium		medium		high-low
			Panel A: size				
exret	-0.072 **	(-6.00)	-0.046 **	(-4.73)	-0.024	(-1.27)	0.048
exret*news	0.072 **	(4.78)	0.028 **	(2.74)	0.014	(1.32)	-0.058
exret*abturn	-0.004	(-0.84)	-0.013 ˆ	(-1.74)	-0.001	(-0.05)	0.003
exret*news*abturn	0.010	(1.29)	0.021 **	(2.65)	-0.001	(-0.07)	-0.011
			Panel B: book-to-market				
exret	-0.049 **	(-4.87)	-0.040 **	(-3.46)	-0.037 **	(-2.76)	0.011
exret*news	0.025 **	(2.81)	0.022 *	(2.17)	0.027 *	(2.22)	0.001
exret*abturn	-0.006	(-0.91)	-0.014	(-1.91)	-0.002	(-0.23)	0.004
exret*news*abturn	0.014 *	(2.06)	0.021 **	(2.86)	0.011	(1.31)	-0.003
			Panel C: past return				
exret	-0.036 **	(-2.99)	-0.051 **	(-4.66)	-0.046 **	(-3.87)	-0.011
exret*news	0.023 **	(2.05)	0.043 **	(4.40)	0.012	(1.23)	-0.011
exret*abturn	-0.011	(-1.45)	-0.009	(-1.37)	-0.003	(-0.40)	0.008
exret*news*abturn	0.015 ˆ	(1.86)	0.012	(1.61)	0.019 **	(2.56)	0.004
			Panel D: analyst coverage				
exret	-0.037 **	(-3.42)	-0.041 **	(-3.38)	-0.045 **	(-3.48)	-0.009
exret*news	0.023 *	(2.13)	0.033 **	(3.09)	0.026 **	(2.66)	0.003
exret*abturn	-0.008	(-1.48)	-0.010	(-1.25)	0.000	(-0.01)	0.008
exret*news*abturn	0.019 **	(2.82)	0.017 *	(2.04)	0.003	(0.36)	-0.015
			Panel E: analyst dispersion				
exret	-0.052 **	(-5.35)	-0.031 *	(-2.52)	-0.033 *	(-2.02)	0.019
exret*news	0.032 **	(3.19)	0.009	(0.90)	0.022 ˆ	(1.74)	-0.010
exret*abturn	-0.008	(-1.14)	-0.019	(-1.87)	0.005	(0.40)	0.013
exret*news*abturn	0.016 *	(2.29)	0.023 *	(2.29)	0.000	(0.02)	-0.016
			Panel F: institutional ownership				
exret	-0.035 **	(-2.65)	-0.040 **	(-3.59)	-0.046 **	(-4.00)	-0.011
exret*news	0.021	(1.43)	0.034 **	(3.32)	0.021 **	(2.41)	0.001
exret*abturn	-0.015 **	(-2.04)	-0.002	(-0.35)	-0.004	(-0.47)	0.011
exret*news*abturn	0.018 ˆ	(1.88)	0.015 *	(1.97)	0.012	(1.55)	-0.006
			Panel G: illiquidity				
exret	-0.044 **	(-4.16)	-0.035 **	(-2.92)	-0.033 *	(-2.01)	0.011
exret*news	0.029 **	(2.78)	0.017	(1.64)	0.026 ˆ	(1.83)	-0.003
exret*abturn	0.016 **	(2.23)	-0.019 **	(-2.60)	-0.035 **	(-3.76)	-0.051
exret*news*abturn	-0.008	(-0.96)	0.025 **	(3.32)	0.012	(0.97)	0.019

Table 2.4: Return reversals - the role of news tone and source

In this Table the key coefficients from Equation 2 are compared for news categories formed on news source and tone. News can be either direct 'wire' news released by companies or 'agency' news provided by outlets such as Reuters. Consequently, any given news day can contain only 'wire' or 'agency' news, or both. The tone of a news day can be either positive, negative or neutral based on the average tone of individual stories on that day falling into upper, lower or the two middle quartiles of the distribution of tone from the previous quarter. In Panel C, the one of 'wire' and 'agency' stories is compared conditional on whether they occur on the same day or on separate days. The estimates in Panels A and B are obtained from a single panel regression using all eligible observations and including month fixed effects. The dependent variable is stock's i excess return over days $[t+2:t+10]$, which is regressed day t excess return $Exret$, the news indicator $News$, abnormal turnover $Abturn$ and two-way and three-way interactions between these variables. Furthermore the regression includes standard control variables such as $Size$, book-to-market ratio BtM, past returns Mom and past volatility $Pastvol$ as well as the interaction between size and excess return. t-statistics appearing below the coefficients are computed from standard errors clustered on firm and day. Significance levels: * - 5%, ** - 1%

Panel A: univariate sorts on tone and source

	news tone			news source		
	positive	neutral	negative	wire	agency	both
$Exret*News$	-0.0041	0.0285 **	0.0427 **	0.0106	0.0130	0.0507 **
	(-0.36)	(3.06)	(3.55)	(1.14)	(0.90)	(4.69)
$Exret*News$	0.0287 **	0.0085	0.0040	0.0275 **	0.0183 *	-0.0003
$*Abturn$	(3.41)	(1.53)	(0.57)	(3.49)	(1.98)	(-0.05)

Panel B: sorting on tone and source

	positive			neutral			negative		
	wire	agency	both	wire	agency	both	wire	agency	both
$Exret*News$	-0.0042	-0.0107	-0.0024	0.0213	0.0143	0.0389 **	0.0172	0.0143	0.0829 **
	(-0.30)	(-0.45)	(-0.10)	(1.64)	(0.71)	(3.12)	(0.79)	(0.66)	(4.92)
$Exret*News$	0.0364 **	0.0355 *	0.0206	0.0120	0.0220	0.0034	0.0394 **	0.0042	-0.0137
$*Abturn$	(2.63)	(2.11)	(1.65)	(1.10)	(1.74)	(0.56)	(2.61)	(0.32)	(-1.56)

Panel C: average weighted tone of wire and agency news stories

	when issued alone			when issued on the same day		
overall news day tone	wire	agency	diff.	wire	agency	diff.
negative	-0.56	-0.58	-0.02	-0.21	-0.42	-0.21
neutral	0.26	0.22	-0.03	0.37	0.11	-0.25
positive	0.78	0.76	-0.02	0.73	0.70	-0.03

Table 2.5: News characteristics and asymmetric information

This Table documents the importance of various news characteristic for the resolution of asymmetric information. In particular, the count of individual news items per news day (count), the average number of words per news item (words) and the fraction of words identified as related to the company mentioned in the announcement (fraction) are examined. Each characteristic is demeaned by day and size quintile and "count" and "words" are also in logarithms to reduce skewness. The rest of the regression equation is as in Eq. 2.2. The coefficient on "exret*news" measures the effect on reversal of news with the average value on each characteristic. *t*-statistics appearing below the coefficients are computed from standard errors clustered on firm and day.
Significance levels: * - 5%, ** - 1%

.5	Panel A: summary statistics					
	std. dev.		correlations			
count	5.73		1	-	0.069	-0.118
count (if ≤ 5)	1.68			1	-0.0508	-0.075
words	0.78				1	-0.419
fraction	0.29					1
Panel B: impact on the resolution of asymmetric information						
	all days	count ≤ 5	all days	all days	all days	count ≤ 5
exret	-0.0412 **	-0.0392 **	-0.0417 **	-0.0417 **	-0.0418 **	-0.0391 **
	(-3.79)	(-3.57)	(-3.86	(-3.86)	(-3.86)	(-3.56)
exret*news	0.0272 **	0.0313 **	0.0271 **	0.0260 **	0.0343 **	0.0333 **
	(3.75)	(3.19)	(3.75	(3.60)	(2.80)	(3.41)
exret*count	-0.0007	0.0096 **				0.0098 **
	(-1.53)	(2.74)				(2.75)
exret*words			0.0144 **		0.0126 **	0.0129 *
			(3.64		(2.63)	(1.96)
exret*fraction				-0.0467 **	-0.0119	-0.0096
				(-3.90)	(-0.81)	(-0.50)
exret*abturn	-0.0037	-0.0032	-0.0039	-0.0039	-0.0039	-0.0031
	(-0.69)	(-0.59)	(-0.72	(-0.71)	(-0.72)	(-0.59)
exret*news*abturn	0.0126 **	0.0163 **	0.0100 *	0.0097 *	0.0099 *	0.0153 **
	(2.39)	(2.60)	(2.02	(1.94)	(2.00)	(2.45)
Number of Observations	5'456'013	5'272'867	5'456'013	5'456'013	5'456'013	5'272'867
R-square	0.019	0.019	0.019	0.019	0.020	0.021

Table 2.6: Summary of other news characteristics by news tone and news source

To gauge the strength of the association between news tone, news source and other news characteristics, this Table presents average values of the count of individual news items per news day (count), the average number of words per news item (words) and the fraction of words identified as related to the company mentioned in the announcement (fraction). The averages are computed separately for positive, neutral and negative news days and also for wire and agency news. With respect to news source (wire or agency) there is also a possibility that the two types are released on the same day and this is reflected on the right hand side of the Table.

	average value					
	when issued alone			when issued on the same day		
variable = count	wire	agency	diff.	wire	agency	diff.
negative	1.12	2.06	0.94	1.31	3.00	1.70
neutral	1.18	1.99	0.81	1.56	2.78	1.22
positive	1.18	1.33	0.15	1.36	1.49	0.13
variable = words						
negative	914	496	-418	1'668	275	-1'393
neutral	595	345	-250	1'295	267	-1'028
positive	759	439	-320	923	234	-689
variable = fraction						
negative	0.67	0.46	-0.21	0.55	0.67	0.13
neutral	0.70	0.57	-0.14	0.60	0.66	0.06
positive	0.74	0.51	-0.23	0.70	0.73	0.03

Research paper 3

Short-term reactions to news announcements: what do investors learn from them?

Michal Dzielinski

Abstract

This paper extends models of learning about profitability to the case of voluntary disclosure. Using short-window regressions, I first find that the whole company-specific news flow, not just earnings announcements, has the property of providing useful information about other stocks. Consequently, betas of announcing stocks increase significantly in months with some news, especially if the volume of news is unusually high. However, I also find that voluntary disclosure differs from earnings announcements in one important respect. While for the latter the sign of the news is not important, it is only negative non-earnings news that has a significant impact on beta. This is consistent with theoretical predictions concerning incentives of managers to withhold negative news, which subsequently leads to disclosure "bunching".

3.1 Introduction

In this paper, I study ten years of news released by and about companies listed on the New York Stock Exchange, a dataset of almost 1.5mln announcements. In the first step, I examine whether relating daily returns to news generates the kind of cross-sectional patterns that would be expected based on stock characteristics, such as size and visibility, and news characteristics, such as informational content and contribution to the resolution of uncertainty. Then, I study whether the effect of news persists at monthly time horizons and affects the returns of the announcing stock and other stock in the market in a systematic way. With respect to the announcing stock, the analysis is focused on the impact of news on alpha, that is the systematic outperformance of the market. The impact on other stocks is analyzed following a recent contribution by Patton and Verardo (2012), who propose and test a model in which learning about profitability of other companies causes the beta of the company announcing its earnings to increase on the announcement day. The overarching question is whether public financial news enables investors to learn not only about the announcing stock but about other stocks as well.

The main findings of the paper are as follows. First, the learning effect of news extends to the monthly horizon and to the general news flow, not just earnings announcements. This is based on the fact that betas increase significantly in months with news and the increase is driven by months with above average news flow, measured as the number of days in a month on which news about a given company was released. Both are non-trivial extensions, since on one hand the results of Patton and Verardo (2012) and in the first part of this paper seem to suggest that markets are very efficient at incorporating individual news announcements. However, the effects of multiple announcements over time add up to a significant effect at lower frequencies. On the other hand, earnings are a very special type of announcements and it is not at all clear that their impact should generalize to other types of news as well. Empirically, there is one important difference in that for the general news flow investors appear to learn more from bad news than good news. This is an interesting contribution to the "learning from news" literature, which also includes Savor and Wilson (2011), and which has claimed that for earnings announcements the effect is symmetric.

The critical difference between earnings and other news seems to be that while earnings announcements are pre-scheduled and mandatory, companies have considerable freedom in choosing which other news to release and when. Kothari, Shu, and Wysocki (2009) and Acharya, DeMarzo, and Kremer (2011) give theoretical motivation for the incentive of managers to withhold bad news and disclose it in clusters, that is at a time when other companies are also disclosing similar bad news. For the above reasons, bad news about one company can be seen as more indicative of the news that other companies might also disclose in the near future than good news, which all companies are happy to disclose immediately. Hence, there is significant increase in beta in months with bad news but no similar increase in months with good news. However, that does not mean that good news has no systematic impact on stock prices, just that its effect seems limited to the announcing stocks. This is because alphas in months in which stocks announce positive news are significantly higher than in other months. Thus, the second main result of the paper is to show that different incentives governing the release of good and bad news make the latter more useful for learning about the prospects of other stocks.

The separate analysis of good and bad news was made possible by applying automatic text-processing algorithms to all relevant announcements made over the period from January 2003 till December 2011. Through the use of such processing and by showing the asymmetry in how good and bad news impacts medium-term returns, the paper also contributes to the growing literature on the role of public news in financial markets. Starting with Chan (2003) there has been an interest in how certain properties of stock returns, drift and reversal in his case, depend on the release of company news. Later papers have tended to focus on shorter like (bi-)weekly (Gutierrez and Kelley (2008), Tetlock, Saar-Tsechansky, and Macskassy (2008), Tetlock (2010)), daily (Tetlock (2010)) or even intraday horizons. One notable exception is the study of Sinha (2010) on news and momentum, which also uses the same dataset as this paper. To my best knowledge, this is the first study to use content analysis to separate the alpha and beta channels through which good and bad news are incorporated into stock prices and what effect this has on cross-company learning.

The rest of the paper is organized as follows. Section 2 makes case for using textual analysis news by showing that good / bad news differentiated this way represent significantly positive / negative innovations in the price process. Section 3 discusses how these innovations translate into a systematic effect on stock returns. Section 4 discusses the methodology to empirically verify the implications of the theoretical discussion. Section 5 presents the results, followed by robustness checks in Section 6. The final section concludes.

3.2 Short-term reactions to news announcements

To determine when there was news about companies listed on the NYSE, I use the information provided in the Thomson Reuters News Analytics database. It contains the complete archive of company-specific news announcements published by Reuters on any of its financial services since January 2003. The database also covers announcements made by companies directly to investors via channels like the PR Newswire and BusinessWire. At the end of 2011 it contained around 13mln announcements for 20'000 stocks worldwide. NYSE stocks were responsible for $\sim 12\%$ of the news flow, the highest share for any exchange in the world, commensurate with their large weight in global market capitalization. Table 3.1 reports the number of news and news days for all stocks as well as for quintiles sorted on relevant stock characteristics. Given that there are 2'919'421 daily observations in the sample, there is roughly one news day for each five trading days on average but his proportion varies significantly along the size dimension. Size is defined as the logarithm of market cap (price times shares outstanding) computed at the end of June each year. The largest stocks dominate the news flow with $\sim 60\%$ of all news announcements being released in the top quintile. For this reason, the other subsample sorts are performed on a size-adjusted basis. The procedure for size adjustment follows Tetlock (2010) that is all stocks are first sorted on size and then, within each size group, on e.g. analyst coverage. Finally, stocks with the least analysts from each size quintile form the lowest analyst coverage quintile and so on. Analyst coverage is defined as the number of analysts issuing a forecast before each quarterly earnings announcement. More analysts coverage generates more news independently of size, which seems intuitive, but interestingly so does analyst dispersion. This is defined as the standard deviation of quarterly earnings forecast. It appears related to the 'differences of opinion' interpretation of analyst dispersion suggested by Diether, Malloy, and Scherbina (2002). If investors hold diverse opinions about a stock, they are more likely to express them than if they agree, in which case they would just reiterate the opinions of others. Finally, the last panel of Table 3.1 provides tentative evidence that public news is associated with information arrivals, because news days tend to cluster in periods of high abnormal turnover, which has been used to proxy for information entering the market in numerous earlier studies (Kim and Verrecchia (1991), Gervais, Kaniel, and Mingelgrin (2001), Llorente, Michaely, Saar, and Wang (2002)). Daily abnormal turnover is calculated as the log of daily turnover (shares volume divided by shares outstanding), de-trended using the 60-day average of log turnover[1]. Then, the daily observations are averaged across the month to arrive at the final proxy used to construct the ranking.

The major benefit of using news data from Thomson Reuters is that the texts of the announcements have been processed by a linguistic algorithm and evaluated for positive and negative tone. The objective of the procedure is the same as in the related literature analyzing the role of public news in financial markets - to quantify language and develop a numerical measure summarizing the content of text, where the fact whether the text was positive or negative tends to be the most important dimension. Tetlock (2007) and **?** have popularized the fraction of negative words, as defined in Harvard-IV4 sociolinguistic dictionary, as one such measure, which was also used by e.g. Engelberg (2008) and Graf

[1]To avoid the problem of zero daily turnover, I add a small constant to each daily value before taking logarithms. The magnitude of this constant, 0.00000255, is chosen as to make the distribution of turnover closer to normal, see Llorente, Michaely, Saar, and Wang (2002) and Richardson, Sefcik, and Thompson (1986)

(2011). This approach was refined by Loughran and McDonald (2011) who argue that certain words like 'liability' can have a different tone in financial context than in the general language and proposed an alternative dictionary more suitable for finance. Davis, Piger, and Sedor (2006) and Demers and Vega (2011) use software called DICTION, which also uses word lists to look for features like optimism and certainty. Finally, Jegadeesh and Wu (2011) develop a methodology based on the price impact of certain words in the past. TS The measure provided by Thomson Reuters is based on the probability of the news being positive, negative or neutral with respect to a certain company. Depending on which probability is the highest, the whole news item is categorized as positive (+1), negative (-1) or neutral (0) *for that company.* The probability is assessed by comparing the text to a "learning set" of Reuters news, which has been scored by Reuters reporters. As such, it is a supervised learning approach, very popular in natural language processing[2]. Its main advantages are specificity to finance (because the algorithm was trained on financial news) and the capability to analyze tone with respect to individual companies thanks to the use of techniques such as parts-of-speech tagging (to understand which words are nouns, verbs etc.) and named entity recognition (to understand which words refer to e.g. company names). Details of the procedure are provided in a white paper by ThomsonReuters (2008). Earlier studies using this data, which include Groß-Klußman and Hautsch (2011), Storkenmaier, Wagener, and Weinhardt (2012) and Sinha (2010), have shown its usefulness both in high-frequency and multi-day settings.

To more formally make the case that public news represents innovations in the price process and that linguistic tone is a reasonable measure of content, I first construct a daily measure of news tone. To this end I net positive and negative news against each other using the following formula:

$$Tone = \frac{\sum 1 \cdot prob_{pos} + \sum(-1) \cdot prob_{neg}}{n_{pos} + n_{neut} + n_{neg}} \in [-1; 1] \tag{3.1}$$

In the next step, a news *day* is categorized as positive if the daily tone is in the highest 25% of the previous quarter's distribution of news tone. It is negative if it belongs to the lowest 25% and it is considered neutral if it falls in between. This procedure is similar to Tetlock, Saar-Tsechansky, and Macskassy (2008) and is intended to reflect the fact that the benchmark for positive and negative might be changing over time. For the whole sample this leads to a natural distribution, where half of the news days are neutral and the other half are approximately equally split among positive and negative (see columns 3-5 in Table 3.1). In the cross section, it is interesting to note that large stocks, stocks with more analyst coverage, but especially stocks with higher analyst dispersion tend to have more negative

[2]Jurafsky and Martin (2008) offer a comprehensive introduction into the theory and applications in this field

news.

To obtain return innovations, I use residuals ($\epsilon_{i,t}$) from short-window regressions from the Fama and French (1993) three-factor model:

$$Ret_{i,t} = \alpha_i + \beta_{1,i} \cdot MKT_t + \beta_{2,i} \cdot SMB_t + \beta_{3,i} \cdot HML_t + \epsilon_{i,t} \tag{3.2}$$

where $Ret_{i,t}$ is the return of stock i on day t and MKT, SMB and HML are daily returns of the market, size and value factor from Kenneth French data library. The regressions are estimated for each stock and month separately to take into account time-varying risk exposures.

Finally, the residuals from all monthly regressions are stacked together and regressed on three news day dummies, each of which is equal to 1 if day t had news for stock i with the overall tone positive, negative or neutral respectively, and equal to 0 otherwise. Since residuals from all regressions are pooled together, standard errors are clustered along the stock dimension to control for possible autocorrelation. Given that the mean of three-factor residuals is zero by construction, the coefficients on the news day dummies represent deviations from this mean and the question is whether they are significantly large and in the direction indicated by tone. The last three columns in Table 3.1 show that this is indeed the case in the whole sample and also in all analyzed subsamples. There is however considerable heterogeneity in the cross-section with both positive and negative news generally being associated with larger excess returns in higher quintiles of analyst coverage, analyst dispersion and abnormal turnover. Thus, news has more impact for stocks with more visibility, more uncertainty and more abnormal trading, which is consistent with public news bringing new information to the market. The fact that the significance persists into the largest quintile of stocks, for which news days are a very common occurrence, is further evidence of the robustness of news impact.

3.3 Systematic impact of news

The overall conclusion from the previous section is that public news represent significant innovations in the price process and linguistic tone is a good way to capture the *ex ante* content of news. In this section I turn to the question of whether news about a company is important only for its own stock or whether it also impacts stocks of other companies. A related question is whether the impact of news is only transitory and limited to the news day itself or whether it is also discernible at longer time horizons.

The way to think about the second question is fairly straightforward. If news has a systematic impact on stock returns, then this should show up as a significantly positive (negative) constant term (alpha) during periods with positive (negative) news. In other words, all or most of the daily returns within a month should be shifted in the direction indicated by the news, not just returns on the news days themselves.

Answering the first question is more involved. An appropriate framework has been suggested by Patton and Verardo (2012) and is based on studying the changes in the market beta of stocks around news announcements. The argument is that if news released about stock i is informative for other stocks, this will increase the co-movement between stock i and the rest of the market and an observable consequence will be an increase in its market beta. The underlying assumption is that returns of all stocks in the market contain a common component, which makes it possible to infer information about stock j by studying announcements related to stock i. On the other, the fact that announcements for different companies arrive asynchronously creates the need for such cross-company learning. Empirically, by computing realized betas from high-frequency returns, they find that beta indeed spikes up on news days, an effect that is stronger for more visible stocks, stocks more correlated with the economy and for news that is more informative and resolves more uncertainty all of which support the learning hypothesis. The main limitation of their analysis is the fact that the stock sample contains only stocks from the S&P 500 and the news sample contains only earnings announcements, thus covering a relatively small fraction of the company and news universe.

Extending the analysis to the general news flow is a non-trivial step, because earnings announcements differ from voluntary disclosure in several important ways. First of all, earnings have a strong quantitative component, which makes it considerably easier to determine the content of such announcements as positive or negative and also assess the relevance for other stocks. It is not clear that investors are able to accomplish a similar assessment for mostly qualitative information embedded in other news releases. Furthermore, earnings announcements are mandatory and pre-scheduled. The fact that they are mandatory means that, aside from outright manipulation, companies have to disclose whatever information they have at a particular time, whether good or bad. All other disclosures by contrast are either voluntary or subject to rather general materiality requirements. Thus, it is likely that companies will be happy to disclose all kinds of good news they have but only those bad news for which they consider the materiality constraint to be binding, due to regulatory, litigation or reputational risk. Kothari, Shu, and Wysocki (2009) develop a model in which managers accumulate bad news until it reaches a certain threshold, while good news is released immediately. This intuition seems to hold well in reality. For a large sample of announcements made directly by US companies through outlets such as PR Newswire or Businesswire, Dzielinski (2012) finds the proportion of good to bad announcements to be roughly four to one, even during the financial crisis.

The fact that managers may have incentives to withhold bad news makes the issue of strategic timing important for cross-sectional patterns in information disclosure. Again, it is largely absent for earnings announcements, for which the dates are relatively inflexible and to a large extent determined in advance with only minor deviations, but relevant for voluntary disclosure, where the freedom of when to announce is much greater. Acharya, DeMarzo, and Kremer (2011) show that if the arrival of information to managers cannot be monitored, and thus they can choose when to *release* it, this will induce clustering in the release of bad news but not good news.

The conclusions from this discussion cast doubt on whether one of Patton and Verardo (2012) predictions that the sign of the news does not matter for stock beta only its 'size' (that is the new information content it delivers to investors) should hold outside the special case of earnings announcements. First, investors might recognize that good news is released more eagerly and thus has a lower informational value. This is the materiality aspect mentioned above. To see the effect of news timing, consider an investor observing two stocks, i and j, and assume that i releases a piece of good news. Then, knowing that companies like to release good news as soon as they have some, a rational investor would conclude that if j also had some good news it would have disclosed it already. In other words, the probability of j also having some good news it did not disclose yet is low, so the informativeness of good news about i for j is limited. The situation changes however were i to issue bad news. There, the investor has good reasons to suspect that j is also withholding some bad news and there is much more to be learned about j by analyzing i's news. Empirically, this would translate into betas increasing more with bad news that good.

3.4 Methodology

The approach to study the response of market alphas and betas to news in this paper is based on monthly regressions using daily returns. This is in contrast to Patton and Verardo (2012), who estimate daily betas from high-frequency returns sampled every 25 minutes. The difference is on one hand due to the fact that it is difficult to obtain reliable high-frequency data for the whole NYSE universe of stocks. On the other hand this approach is appropriate, because the focus of the paper is on the importance of the broader company newsflow rather than specific point-in-time events like earnings announcements. Monthly betas have been commonly used to study short-term variations in risk factor sensitivities (e.g. Pàstor and Stambaugh (2003), Lewellen and Nagel (2006)). Ang, Hodrick, Xing, and Zhang (2006) call it "a natural compromise between estimating coefficients with a reasonable degree of precision and pinning down conditional coefficients in an environment with time-varying factor loadings". Thus, it is not unreasonable to expect monthly betas to be affected by the total flow of news during the month. Moreover, this approach is conservative in that it is biased against finding significant results. The estimation of beta is based on the standard CAPM regression:

$$Ret_{i,t} = \alpha_i + \beta_i \cdot MKT_t + \epsilon_{i,t} \tag{3.3}$$

where $t \in T$ denote daily observations within month T and Ret_i is the return on stock i and ret_M is the excess return on the market portfolio, both including dividends. Similarly to previous literature the focus is on NYSE stocks to avoid microstructure issues typical for NASDAQ and (usually small) AMEX stocks. I also require at least 15 daily observations with positive trading volume for the calculation. Performing the above regression for every stock-month in the sample yields 116'139 monthly estimates of beta for 1'420 distinct stocks. Table 3.2 presents the averages of beta, alpha, size and monthly return for all stocks in the sample as well as for size quintiles. Consistent with asset pricing theory, smaller stocks earn higher returns and have higher CAPM alphas. They are however also more risky, as evidenced by higher average betas. The beta estimates are then related to news arrivals via the following baseline regression:

$$\beta_{i,T} = Intercept_i + \delta_1 \cdot News_{i,T} + \delta_2 \cdot Size_{i,T} + \epsilon_{i,T} \tag{3.4}$$

where $News_{i,T}$ is a dummy variable equal to 1 if there was some news about stock i in month T, according to the Thomson Reuters News Analytics database, and 0 otherwise. $Size$ is the monthly average of the natural logarithm of daily market capitalization (defined as price times shares outstanding) of stock i. In other words, it is a panel regression, which examines the average difference between betas in months with and without news, while controlling for the effects of size, which has been shown in Table 3.2 to be a major determinant of stock beta. Regression 3.4 uses observation pooled from all stocks, so firm fixed effects are included to control for the considerable heterogeneity in company betas. Note that in this setting the $Size$ variable captures the average impact of fluctuations of company size over time, rather than its cross-sectional variation.

An empirical problem with this type of regression design using monthly observations has already been anticipated by Chan (2003) - that due to expanding coverage no-news months become a rare occurrence, thus making any reasonable comparison with news months impossible. The last four columns of Table 3.2 provide evidence that this is indeed relevant for my sample, which contains only $\sim 13\%$ of no-news months and the proportion drops to a mere 2% in the top size quintile. To overcome this issue, I split the news dummy in the spirit of Fang and Peress (2009) into two separate dummies, $News^1$ and $News^2$, indicating whether the news flow in a given month T was below or above the sample mean for stock

i, where news flow is measured by the number of news days during the month. In this way I can distinguish between different levels of news intensity, taking into account the fact that the baseline intensity is very heterogenous across stocks. The conjecture is that more intensive news flow will have a more pronounced effect on stock beta.

3.5 Empirical results

The results in Table 3.3 are consistent with the learning literature in that news events increase the beta of a stock in a statistically and economically significant way. The economic significance can be judged by the fact that for the average stock the news effect is comparable in magnitude to a 16% change in size (a 0.015 increase in a news month vs. a -0.107 decrease per unit increase in the log of market capitalization). Closer examination reveals that it is indeed months with intensive news flow driving the results with the estimate on $News^2$ more than twice as large as the pooled one and the estimate on $News^1$ completely insignificant. This suggests that months with below average news flow can be considered no-news months, since they do not appear very informative anyway. The last column of Table 3.3 shows that months with above average news flow still have significantly higher betas than this combined group. The upshot is that both groups are now roughly equal in size, improving the statistical properties[3] of any comparisons, especially in subsamples.

Looking into the cross-section of stocks provides evidence consistent with the learning explanation for the increase in betas. This argument predicts that more visible stocks and stock more correlated with the broader economy should generate a stronger learning effect and thus experience larger increases in beta. Proxying the correlation with the economy by size and visibility by size-adjusted analyst coverage clearly shows that stocks from the two top quintiles are the most affected by news. Considering a large universe of all NYSE stocks also allows to examine just how far down the ladder does the learning effect reach. It appears that stocks, which score medium on analyst coverage (quintile 3) still show a pretty substantial effect. Analyst coverage also seems to be a more important factor that market capitalization, where the effect dissipates more quickly and is only significant at the 10% level in the middle quintile. On the other hand, it should be the case that more informative news and news resolving greater uncertainty has more impact. Defining informativeness for news which generally does not have a strong quantitative component (like earnings announcements do) is challenging - the tone variable described in Section 2 does a good job at differentiating between positive and negative news but both of those can be either important or unimportant, so a different measure is needed. The importance of news is associated with the provision of new information to the market and this points to

[3]Large samples are for instance less sensitive to outliers

average abnormal turnover during the respective month as a reasonable proxy. The amount of uncertainty is proxied by the dispersion of analyst earnings forecasts, which is arguably a measure valid not only for earnings announcements. The results along these two dimensions line up very well with theory. The impact of news on beta increases monotonically from the lowest quintile and reaches considerable magnitudes in the highest one.

Overall, the results so far support the alternative methodology I propose in that it captures the impact of news on beta rather well. They also show that with respect to the general news flow the effect that news about a company has on learning about other companies is still visible at the monthly frequency.

3.5.1 News tone and the systematic impact of news

The main hypothesis of the paper is that due to different incentives facing managers with respect to its release, good and bad news will have different learning value and thus a different impact on beta. To examine this hypothesis, the $News^2$ dummy from Eq. 3.4 is interacted with three dummy variables for good, neutral and bad news months. A good news month is defined as having no days with bad news and some days with good news. A bad news month is defined analogously. Months having no good or bad news days as well as those with both types are categorized as neutral. The modified regression equation is as follows:

$$\begin{aligned}\beta_{i,T} = Intercept_i + \delta_2^{pos} \cdot News^2_{i,T} \cdot Pos_{i,T} + \delta_2^{neut} \cdot News^2_{i,T} \cdot Neut_{i,T} + \delta_2^{neg} \cdot News^2_{i,T} \cdot Neg_{i,T} + \\ + \delta_3 \cdot Size_{i,T} + \epsilon_{i,T}\end{aligned} \tag{3.5}$$

Therefore, it compares the betas in moths with above average news flow *and* the respective tone to betas in other months. Similarly to the baseline specification, it is estimated in the whole sample and in subsamples related to the hypothesized impact of news. The results in Table 3.5 clearly show that the increase in beta in substantially bigger in bad months than in good months. In fact, in good months there is no significant increase at all. The middle category of months, which were neither clearly negative not positive behaves more like the negative group and betas increase significantly. This further underscores the fact that positive news is not very useful for learning across companies. The same pattern holds in the whole sample as well as in all relevant subgroups (i.e. those for which a significant impact of news as such could be previously established) sorted on size, analyst coverage, abnormal turnover and analyst dispersion.

If positive news has little or no impact on beta, does that mean it has no systematic impact on stock returns at all? To answer this question, I turn to examine the second output of the CAPM regression, which is the stock alpha. The analysis of stock alphas works analogously to the analysis of betas, that is the monthly estimates are regressed on the $News^2$ variable, interacted with dummies for positive, negative and neutral months. The regressions also include stock size as a control variable and firm fixed effects to allow for heterogeneity in stock alphas. The results in Table 3.6 show a clear pattern of alphas, which are significantly more negative (positive) in months with bad (good) news than in other months. Neutral months are associated with average alphas undistinguishable from other months, which is consistent with the intuition that news, which is either conflicting (in the sense of good and bad news being released during the same month) or has no clear direction cannot impact stock returns in a systematic fashion. However, the important observation is that positive news about stock i does have a systematic effect on the returns of stock i, namely it increases its alpha with respect to the market. In fact, the magnitude of the change in alpha is larger in good months that in bad months. This relationship is true in the whole sample as well as in most of the analyzed subsamples. It lends further support to the hypothesis that good news is informative but its informativeness is mostly limited to the announcing company, because other companies have no incentive to withhold good news and so there is little potential to learn something new about them.

3.6 Robustness

In this section the sensitivity of the main findings, that beta increases in news months particularly in bad news months, is investigated with respect to modifying the original setup through adding more control variables to the regression and changing the way good and bad news is categorized. Finally, an attempt is made to assess the importance of earnings announcements for the overall results. All the results reported here are based on the $News^2$ variable that is they compare months with above average coverage to those with either below average or no coverage at all.

3.6.1 Additional control variables

Several aspects come into consideration when choosing the additional controls. First, the results could potentially be due to autocorrelation in betas, thus one lag of monthly beta is included. Otherwise, it could also be a consequence of stock volatility, because more volatile stocks also tend to be more risky and have higher betas. Monthly stock-specific volatility is approximated by the sum of squared residuals from the three-factor regressions described in Section 2. For similar reasons, monthly market volatility, computed as the sum of squared daily excess market returns, is also included. Finally, raw monthly turnover is added as well. The results after augmenting the regressions in equations 3.4 and 3.5 are reported in the first column of Table 3.7. The additional controls act to reduce the initial estimates of news impact on beta but do not qualitatively change either of the main conclusions.

3.6.2 The role of earnings announcements

In Section 3 the difference between earnings and other types of announcements was discussed and how that might affect the predictions concerning the behavior of betas. All the results that followed were presented for a sample, which in fact included both earnings and non-earnings news and a perfect separation of the two is not possible at the monthly frequency, because especially the days before and after earnings announcements tend to be populated with other releases. However, under the assumption that the importance of earnings announcements is big enough to influence the entire news flow around these dates, it might still be interesting to compare months in which earnings were announced with other months. This is shown in the second and third column of Table 3.7. The dates of earnings announcements were taken from I/B/E/S and complemented with Compustat for stocks without analyst coverage. Unconditionally, beta increases by more in earnings months that in other news months. Splitting by tone also reveals that the asymmetry between good and bad news is concentrated in the non-earnings months. For the earnings months, both good and bad news is associated with significant increases in beta. This is the most direct evidence that earnings and other news differs fundamentally with respect to learning across companies.

3.6.3 Different measure of positive and negative news

The procedure to categorize news days as positive or negative based on comparing the tone of news on day t with the distribution over the previous three months masks the fact that in absolute terms there is much more positive than negative news. In other words, a sizeable proportion of neutral news days would have been classified as positive based on raw tone probabilities, without relating them to past tone. Under this alternative procedure, all days with average tone above 0.33 are classified as positive and those where it is below -0.33 as negative. The middle range is reserved for neutral news days as before. The aggregation from news days to news months is also left unchanged. Still, around 25% of news months need to be reclassified and the shift is entirely from neutral towards positive and from negative towards neutral. As a result, the number of neutral news moths is almost the same (though these are largely different months) but there are almost 5 times more good months than bad. Despite this significant rotation, the results are unchanged or even stronger, with beta increasing even more during bad months. Another apparent feature is that the alpha during bad months is now significantly lower, suggesting that such exceptionally bad news is to a lesser extent accommodated through the beta channel.

3.7 Conclusions

There is mounting evidence that public news is an effective carrier of genuinely new stock-specific information. These results are the effect of improved, automatic methods of analyzing textual content which make it possible to "quantify language" of hundreds of thousands of company announcements. The question whether these individual announcements combine over time to produce systematic effects on the returns of announcing stocks or in fact also other stocks has scarcely been researched so far. In particular, this is the first study I am aware of that combines textual analysis of a comprehensive set of company announcements with the study of stock alpha and market beta in order to see to what extent news enters through the individual and the systematic channel. Especially changes in beta around news releases have been linked to cross-company learning about profitability, based on quarterly earnings announcements. This paper generalizes the results to the case of voluntary disclosure (i.e. almost all other news except earnings announcements) and shows that there is an additional aspect to non-earnings news. Due to different incentives governing the voluntary release of good and bad news - it is always desirable to issue good news but it often requires the crossing of a certain material threshold before bad news is released - there is an asymmetry in the link between news tone and stock beta. While betas increase significantly in periods with bad news, indicating that investors are learning about other stocks from such news, there is no such effect for good news. The fact that there is apparently not much to learn about other companies from good news of a particular company becomes clear when one considers that learning can only work if those other companies do not release their own news - and they would release their own good news if they had some. However, good news still affects the other systematic component of stock returns, the alpha. This supports the earlier conclusions in that good news is not unimportant. Rather its influence is limited to the announcing company.

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Table 3.1: Excess returns on news days

The Table presents basic news flow statistics for the whole sample as well as for relevant subsamples. The sample period is April 2003 - December 2011. The variables used to construct the subsamples are:

- size, the average market capitalization
- analyst coverage, the number of analysts issuing forecasts before the most recent earnings announcement
- analyst dispersion, the standard deviation of forecasts issued before the most recent earnings announcement
- abnormal turnover, computed following Llorente, Michaely, Saar, and Wang (2002) as described in the text

The ranking on size is updated at the end of June each year, the two analyst-based ranking after each earnings announcement and the ranking on abnormal turnover at the end of every month. Mean excess returns are computed from a regression of daily residuals from the Fama and French (1993) three factor model on dummies for positive, neutral and negative news days respectively. The residuals are obtained from fitting the three-factor model to each stock separately in each month. t-statistics are computed from standard errors clustered by stock and day.
Significance levels: * - 5%, ** - 1%

	number of	number of	number of news days			mean excess return on news days		
quintile	stocks	news	positive	neutral	negative	positive	neutral	negative
			Panel A: all stocks					
	1'898	1'440'844	124'856	297'828	145'368	0.21%	0.15%	-0.19%
						(18.98)	(21.50)	(-16.91)
			Panel B: by size					
1	378	69'116	3'510	6'517	3'726	1.44%	1.07%	0.30%
						(9.02)	(9.28)	(1.52)
2	480	112'842	4'405	9'038	4'766	0.66%	0.37%	-0.27%
						(5.61)	(6.11)	(-2.54)
3	551	152'124	8'032	17'147	8'046	0.46%	0.29%	-0.32%
						(9.28)	(6.99)	(-4.87)
4	793	239'800	22'480	52'799	22'355	0.24%	0.20%	-0.32%
						(13.14)	(11.73)	(-12.99)
5	898	866'962	86'429	212'327	106'475	0.10%	0.09%	-0.14%
						(15.83)	(16.90)	(-15.97)
			Panel C: by analyst coverage					
1	983	183'994	18'937	39'817	17'247	0.10%	0.11%	-0.15%
						(8.49)	(8.64)	(-7.89)
2	1'367	202'667	20'104	45'929	20'955	0.17%	0.11%	-0.16%
						(10.47)	(8.14)	(-7.47)
3	1'379	265'664	22'921	54'993	25'101	0.13%	0.15%	-0.16%
						(9.99)	(11.51)	(-8.33)
4	1'287	319'773	23'915	60'210	30'223	0.17%	0.12%	-0.19%
						(9.65)	(9.72)	(-10.22)
5	986	373'041	25'057	66'820	36'024	0.17%	0.14%	-0.19%
						(11.22)	(10.81)	(-9.93)
			Panel D: by analyst dispersion					
1	1'022	191'023	18'470	37'946	17'004	0.12%	0.11%	-0.07%
						(8.04)	(9.53)	(-3.90)
2	1'124	232'426	21'080	46'759	21'354	0.10%	0.10%	-0.08%
						(9.75)	(10.90)	(-5.97)
3	1'176	243'770	22'163	52'334	23'422	0.12%	0.13%	-0.13%
						(10.02)	(12.55)	(-7.92)
4	1'187	270'724	22'292	55'520	25'859	0.15%	0.12%	-0.19%
						(12.04)	(10.89)	(-12.12)
5	1'007	354'800	19'328	58'981	35'388	0.31%	0.20%	-0.39%
						(12.45)	(10.49)	(-14.34)
			Panel E: by abnormal turnover					
1	1'408	195'010	20'525	44'589	21'978	0.11%	0.10%	-0.17%
						(8.12)	(7.24)	(-7.20)
2	1'393	276'012	25'119	58'427	27'846	0.11%	0.12%	-0.14%
						(8.81)	(10.20)	(-8.49)
3	1'384	312'534	25'648	63'477	29'695	0.13%	0.12%	-0.17%
						(10.68)	(10.19)	(-10.05)
4	1'388	307'694	25'186	62'735	29'869	0.15%	0.11%	-0.18%
						(10.22)	(9.28)	(-9.43)
5	1'413	295'518	21'693	55'608	29'497	0.20%	0.15%	-0.21%
						(8.79)	(10.01)	(-9.44)

Table 3.2: Summary statistics

The table presents mean values of size, monthly return as well as alpha and beta estimates from the short-window CAPM regressions averaged across the whole sample and individual size quintiles. Because stocks can change their size quintile over the sample period, the number of distinct stocks in the whole sample is less than the sum of distinct stocks from all quintiles. Additionally, the number of months and the number of months with news is given - 'below mean' refers to months in which the number of news days was below the sample average for a particular stocks and 'above mean' when it was equal to or above that average. The sample period is April 2003 - December 2011.

	number of stocks	mean size ($ mln)	mean return	mean alpha	mean beta	number of months	with news	below mean	above mean
Panel A: all stocks									
	1'420	2'018	1.38%	0.33%	1.176	116'139	101'372	65'611	35'761
Panel B: by size quintile									
1	454	211	1.93%	0.74%	1.264	20'192	14'349	10'309	4'040
2	615	750	1.50%	0.19%	1.377	22'111	18'189	12'427	5'762
3	626	1'686	1.39%	0.27%	1.211	23'478	20'561	13'599	6'962
4	561	3'715	1.12%	0.22%	1.072	24'974	23'333	14'677	8'656
5	374	18'770	1.08%	0.28%	1.002	25'384	24'940	14'599	10'341

Table 3.3: Beta and news

The table reports parameter estimates from the following regression:

$$\beta_{i,t} = Intercept_{i,t} + \delta_1 \cdot News_{i,t} + \delta_2 \cdot Size_{i,t} + \epsilon_{i,t}$$

where $\beta_{i,t}$ is the CAPM beta of stock i in month t calculated using daily returns within that month, $News_{i,t}$ is a dummy variable equal 1 if stock i had at least one news day in month t (according to the Thomson Reuters News Analytics database) and 0 otherwise, $Size_{i,t}$ is the average of the natural logarithm of daily market capitalization (price times shares outstanding) of stock i in month T. To account for varying intensity of news flow, models (3)-(5) use two news dummies instead of one: $News^1_{i,T}$ ($News^2_{i,T}$) is equal to 1 if the number of news days for stock i in month T is below (above) the average number for stock i over the entire sample period. The regression is estimated using all stock-month observations over the sample period (April 2003 - December 2011). All regressions include firm fixed effects. In models (1)-(4) the coefficient on the news dummy should be interpreted as the average difference in beta between news months and no-news months. In model (5) it is the difference in beta between months with above average news flow and months with either below average or no news flow pooled together. t-statistics appearing in parentheses are computed from standard errors clustered by month.
Significance levels: * - 5%, ** - 1%

	(1)	(2)	(3)	(4)	(5)
$News$	0.006	0.015 *			
	(0.78)	(2.14)			
$News^1$			-0.001	0.007	
			(-0.17)	(1.01)	
$News^2$			0.022 **	0.035 **	0.029 **
			(2.81)	(4.48)	(6.47)
$Size$		-0.107 **		-0.108 **	-0.108 **
		(-26.20)		(-26.42)	(-26.40)
Nobs	116'139	116'139	116'139	116'139	116'139
R-squared	0.243	0.247	0.243	0.248	0.248

Table 3.4: Cross-sectional impact of news on beta

The two panels of the table refer to the parameter estimates from the following regression:

$$\beta_{i,t} = Intercept_{i,t} + \delta_1 \cdot News^2_{i,t} + \delta_2 \cdot Size_{i,t} + \epsilon_{i,t}$$

where $\beta_{i,t}$ is the CAPM beta of stock i in month t calculated using daily returns within that month, $News^2_{i,t}$ is a dummy variable equal 1 if the number of news days for stock i in month T was above the median number for that stock over the entire sample period (see previous Table for a detailed discussion) and $Size_{i,t}$ is the average of the natural logarithm of daily market capitalization (price times shares outstanding) of stock i in month T. The regression are estimated over the sample period (April 2003 - December 2011) for stocks sorted on various characteristics defined in Table 3.1. All regressions include firm fixed effects. In models (1)-(4) the coefficient on the news dummy should be interpreted as the average difference in beta between news months and no-news months. In model (5) it is the difference in beta between months with above median coverage and months with either below median or no coverage pooled together. t-statistics appearing in parentheses are clustered by month.
Significance levels: * - 5%, ** - 1%

all stocks	quintile	size	abnormal turnover	analyst coverage	analyst dispersion
		Panel A: $News^2$			
0.029 **	1	-0.017	0.015	0.004	-0.009
(6.47)		(-0.98)	(1.43)	(0.40)	(-0.93)
	2	-0.002	0.014	0.009	-0.006
		(-0.18)	(1.56)	(0.97)	(-0.58)
	3	0.017	0.037 **	0.023 *	0.021 *
		(1.90)	(4.12)	(2.30)	(2.20)
	4	0.021 **	0.040 **	0.032 **	0.031 **
		(2.76)	(4.26)	(3.27)	(3.08)
	5	0.036 **	0.044 **	0.050 **	0.069 **
		(5.70)	(3.51)	(5.16)	(5.97)
		Panel B: $Size$			
-0.108 **	1	0.102 **	-0.073 **	-0.140 **	-0.090 **
(-26.40)		(8.11)	(-9.24)	(-11.04)	(-7.58)
	2	-0.051 **	-0.108 **	-0.105 **	-0.145 **
		(-3.96)	(-12.30)	(-9.94)	(-12.15)
	3	-0.120 **	-0.097 **	-0.114 **	-0.176 **
		(-9.72)	(-10.27)	(-11.05)	(-15.77)
	4	-0.154 **	-0.108 **	-0.111 **	-0.109 **
		(-13.76)	(-11.05)	(-11.54)	(-9.83)
	5	-0.213 **	-0.146 **	-0.131 **	-0.173 **
		(-23.43)	(-13.47)	(-14.15)	(-17.43)

Table 3.5: The impact of news tone on Beta

In this Table the baseline regression:

$$\beta_{i,t} = Intercept_{i,t} + \delta_1 \cdot News^2_{i,t} + \delta_2 \cdot Size_{i,t} + \epsilon_{i,t}$$

is augmented by interacting the $News^2$ variable with three dummies for positive, negative and neutral months. A month is considered positive if it had at least one positive news day and no negative news days, irrespective of the number of neutral news days. A negative month is defined analogously. All other months are considered neutral. The estimated coefficients are differences between the beta in months with above average coverage (as defined in Table 3.3 and in the text) and the respective tone, and other months. Panels A-D contain the results of the same analysis for subsamples related to the stocks exposure to the broader economy, visibility, abnormal trading and uncertainty. Definitions of the ranking variables are given in Table 3.1. Sample period is April 2003 - December 2011. All regressions include firm fixed effects and t-statistics are computed from standard errors clustered by month.
Significance levels: * - 5%, ** - 1%

all stocks						
	neg	0.048 **				
		(5.91)				
	pos	0.010				
		(1.19)				
	neut	0.028 **				
		(5.04)				
quintuile		1	2	3	4	5
Panel A: sorted on size						
	neg	-0.020	-0.027	0.034 *	0.039 **	0.094 **
		(-0.72)	(-1.35)	(2.12)	(2.77)	(7.35)
	pos	-0.032	0.001	0.006	0.015	-0.010
		(-1.06)	(0.06)	(0.40)	(1.10)	(-0.68)
	neut	-0.004	0.010	0.015	0.016	0.030 **
		(-0.16)	(0.67)	(1.25)	(1.78)	(4.21)
Panel B: sorted on analyst coverage						
	neg	0.021	-0.003	0.014	0.050 **	0.088 **
		(1.08)	(-0.16)	(0.77)	(2.79)	(5.42)
	pos	-0.008	0.022	0.018	-0.011	0.025
		(-0.50)	(1.27)	(0.98)	(-0.60)	(1.26)
	neut	0.004	0.009	0.028 *	0.041 **	0.039 **
		(0.32)	(0.71)	(2.28)	(3.37)	(3.29)
Panel C: sorted on abnormal turnover						
	neg	0.022	0.012	0.074 **	0.073 **	0.059 **
		(1.10)	(0.69)	(4.33)	(4.20)	(2.82)
	pos	0.020	0.014	0.017	-0.001	0.020
		(1.04)	(0.80)	(0.97)	(-0.05)	(0.85)
	neut	0.009	0.015	0.031 **	0.042 **	0.047 **
		(0.71)	(1.32)	(2.76)	(3.66)	(3.02)
Panel D: sorted on analyst dispersion						
	neg	-0.001	0.014	0.022	0.031	0.099 **
		(-0.06)	(0.70)	(1.22)	(1.67)	(5.27)
	pos	-0.010	0.006	0.015	0.012	0.050
		(-0.61)	(0.32)	(0.84)	(0.61)	(1.98)
	neut	-0.011	-0.017	0.023 *	0.038 **	0.059 **
		(-0.93)	(-1.42)	(1.96)	(3.05)	(4.19)

Table 3.6: The impact of news tone on Alpha

In this Table an analogous procedure as for stock beta is applied to explain stock alpha. That is the baseline regression:

$$\alpha_{i,t} = Intercept_{i,t} + \delta_1 \cdot News^2_{i,t} + \delta_2 \cdot Size_{i,t} + \epsilon_{i,t}$$

is augmented by interacting the $News^2$ variable with three dummies for positive, negative and neutral months. A month is considered positive if it had at least one positive news day and no negative news days, irrespective of the number of neutral news days. A negative month is defined analogously. All other months are considered neutral. The estimated coefficients are differences between the alpha in months with above average coverage (as defined in Table 3.3 and in the text) and the respective tone, and other months. Panels A-D contain the results of the same analysis for subsamples related to the stocks exposure to the broader economy, visibility, abnormal trading and uncertainty. Definitions of the ranking variables are given in Table 3.1. Sample period is April 2003 - December 2011. All regressions include firm fixed effects and t-statistics are computed from standard errors clustered by month.
Significance levels: * - 5%, ** - 1%

all stocks						
	neg	-0.94%				
		(-6.93)				
	pos	1.42%				
		(10.23)				
	neut	0.09%				
		(1.02)				
quintuile		1	2	3	4	5
Panel A: sorted on size						
	neg	-0.33%	-1.51% **	-0.79% **	-0.76% **	-0.62% **
		(-0.65)	(-4.40)	(-2.95)	(-3.35)	(-3.14)
	pos	2.52% **	1.33% **	1.48% **	1.14% **	0.85% **
		(4.68)	(3.85)	(5.80)	(5.28)	(3.59)
	neut	0.45%	0.42%	0.08%	0.02%	0.04%
		(1.02)	(1.58)	(0.39)	(0.16)	(0.40)
Panel B: sorted on analyst coverage						
	neg	-0.60%	-0.61%	-0.43%	-0.75% **	-1.43% **
		(-1.87)	(-1.87)	(-1.41)	(-2.54)	(-4.92)
	pos	1.16% **	1.05% **	1.32% **	1.56% **	1.59% **
		(4.27)	(3.46)	(4.43)	(5.13)	(4.45)
	neut	-0.15%	0.02%	0.16%	0.08%	0.16%
		(-0.77)	(0.09)	(0.77)	(0.42)	(0.78)
Panel C: sorted on abnormal turnover						
	neg	-0.46%	-0.46%	-0.13%	-0.95% **	-2.46% **
		(-1.56)	(-1.77)	(-0.48)	(-3.46)	(-6.16)
	pos	1.01% **	0.75% **	0.92% **	1.39% **	2.15% **
		(3.51)	(2.97)	(3.53)	(4.93)	(4.89)
	neut	0.31%	0.04%	0.05%	0.16%	-0.38%
		(1.57)	(0.27)	(0.27)	(0.86)	(-1.28)
Panel D: sorted on analyst dispersion						
	neg	-1.51% **	-0.73% *	-0.99%	-0.08%	-1.34% **
		(-4.80)	(-2.28)	(-3.10)	(-0.24)	(-3.84)
	pos	1.35% **	1.30% **	1.49% **	0.88% **	1.30% **
		(4.92)	(4.39)	(4.70)	(2.47)	(2.78)
	neut	-0.14%	0.39%	0.10%	0.02%	-0.10%
		(-0.74)	(1.90)	(0.50)	(0.07)	(-0.40)

Table 3.7: Robustness checks

In this Table the results concerning the impact of news tone on alpha and beta are investigated for robustness to including more control variables (lagged beta, stock idiosyncratic volatility, market volatility and raw turnover), separating months containing earnings announcements and other months as well as changing the way positive and negative months are categorized (described in the text). Sample period is April 2003 - December 2011. All regressions include firm fixed effects and t-statistics are computed from standard errors clustered by month.
Significance levels: * - 5%, ** - 1%

	adding more control variables		excluding earnings months		excluding non- -earnings months		using different measure of tone	
	alpha	beta	alpha	beta	alpha	beta	alpha	beta
Panel A: all news								
$News^2$		0.012 **		0.026 **		0.048 **		
		(2.86)		(4.77)		(5.92)		
Panel B: separating by news tone								
neg	-1.30% **	0.019 **	-1.05% **	0.037 **	-0.97% **	0.081 **	-2.50% **	0.060 **
	(-9.58)	(2.45)	(-5.91)	(3.45)	(-4.15)	(6.04)	(-10.50)	(4.22)
pos	1.31% **	0.001	1.19% **	0.002	1.41% **	0.038 **	1.24% **	0.010
	(9.50)	(0.18)	(7.07)	(0.22)	(5.37)	(2.54)	(10.78)	(1.50)
neut	-0.02%	0.014 **	0.06%	0.032 **	-0.06%	0.037 **	-0.15%	0.035 **
	(-0.20)	(2.58)	(0.49)	(4.65)	(-0.34)	(3.85)	(-1.67)	(6.50)

Research paper 4

Aggregate news tone, stock returns and volatility

Michal Dzielinski and Henrik Hasseltoft

Abstract

Using a large data set in which the language of millions of firm-specific news items has been quantified, we construct two novel measures: The *aggregate level* of news tone and the *aggregate dispersion* of news tone. High level of news tone is associated with good economic times, high returns, and low volatility. High dispersion of news tone is linked to bad economic times, low returns, and high volatility. We interpret the level and dispersion of news tone as high-frequency measures of economic conditions and economic uncertainty. The two measures forecast aggregate stock returns, realized variance, and the variance risk premium, controlling for various economic and financial variables. Our results suggest that soft firm-specific news matter for aggregate stock prices, in excess of hard information.

4.1 Introduction

The literature on how hard and quantifiable firm-specific information, such as company earnings, impacts stock prices is vast. However, a more recent and growing literature analyzes how soft information in company news can be quantified and how it relates to earnings and stock prices. For example, Davis, Piger, and Sedor (2006), Engelberg (2008), Tetlock, Saar-Tsechansky, and Macskassy (2008), and Demers and Vega (2011) all demonstrate that the tone of firm-specific news items impact stock returns around announcements and predicts future firm earnings and returns. Tetlock (2007) analyzes the content of a popular *Wall Street Journal* column, "Abreast of the Market", using more than 70 word categories from the Harvard IV-4 dictionary and shows that the first principal component constructed from those categories, which loads most heavily on words labeled as negative, predicts lower index returns.

Our contribution is to develop a bottom-up approach of combining the tone of millions of company-specific news items into two measures of aggregate news tone: The aggregate *level* of news tone and the aggregate *dispersion* of news tone. We make use of a database provided by Thomson Reuters News Analytics which contains news tone scores, obtained through linguistic analysis, for all company-specific news announcements released during the period Jan 2003-Dec 2011. Our daily measure of the aggregate level of news tone is constructed by summing the firm-specific news tones across stocks while our measure of daily aggregate news tone dispersion corresponds to the standard deviation of firm-specific news tones across all firms. We also construct corresponding measures on a monthly horizon.

We find a significant negative correlation between the level of aggregate news tone and the dispersion. Moreover, we find that the level of aggregate news tone is positively associated with economic activity and S&P 500 returns while being negatively related to the realized volatility of aggregate stock returns. In contrast, the aggregate dispersion of news tone is negatively correlated with economic activity and aggregate stock returns and positively related to stock market volatility. Furthermore, our two measures are correlated with core financial and economic variables like the VIX index, the Michigan sentiment index, abnormal turnover, changes in aggregate company earnings, and dispersion of earnings forecasts. Interestingly, our two variables are less correlated with the investor sentiment measures developed in Baker and Wurgler (2006) and Baker and Wurgler (2007). This suggests that the aggregate level and dispersion of news tone more reflect rational market forces rather than irrational or sentimental factors.

We find that the level and dispersion of aggregate news tone predict future aggregate stock market returns and realized volatility over both daily and monthly horizons, controlling for various economic and financial variables. Our news tone measures also predict the variance risk premium, indicating that news tone captures a notion of economic uncertainty. Overall, the results indicate that soft firm-specific news matter for aggregate stock prices, in excess of hard information. Most of the predictive power of news tone comes from the dispersion variable which predicts returns negatively and volatility positively. We interpret the dispersion variable as a measure of aggregate information uncertainty since it increases in periods when company news are highly contradictory, with some firms experiencing positive news tones and others negative news tones. Therefore, our findings suggest that aggregate uncertainty about *soft* firm-specific information matters for aggregate stock prices.

The layout of our paper is as follows. Section 2 describes the data. Section 3 presents the empirical analysis and results. Section 4 concludes.

4.2 Data

We construct aggregate measures of news tone and news dispersion using a bottom-up approach. The departing point is the collection of all company-specific news announcements obtained from Thomson Reuters News Analytics. This extensive archive contains all news published either by Reuters or by the companies themselves (via direct outlets like the PR Newswire) in the period between 2003 and 2011.

Each time a company is mentioned in the news, its identifier (Reuters Instrument Code, or RIC) is recorded, together with a precise timestamp. In particular, this means that whenever a news announcement mentions several companies one record per company is created. This is important, because the presentation of each company might be different within the same news story, e.g. good news for Company A might be bad news for its competitors etc. Similarly, the relevance of the news story for each company might be different e.g. with Company A being the main focus of attention, perhaps already named in the headline, while its competitors are only briefly mentioned later in the text.

The linguistic analysis we make use of is capable of grasping such differences. The algorithm developed for this purpose by Thomson Reuters works at the sentence level, identifying the subject (company) and any tone-relevant words related to it. The two procedures it is based on, Named Entity Recognition (NER) and Parts-of-Speech Tagging (POS), have both become standard tools and are widely used in content analysis (e.g., Jurafsky and Martin (2008)). Thus, we are able to track the tone of the news for each company separately, even if they are mentioned in the same text. Another advantage of this algorithm is that it attempts to make sense of syntactic relationship in determining the tone of the news, represented as a classification variable: +1 for positive, 0 for neutral and -1 for negative tone. This can be achieved either by defining explicit grammatical rules (such algorithms are then called *deductive*) or by supplying a training set evaluated by human "teachers", from which the algorithm *inductively* infers the relevant rules. The News Analytics algorithm belongs to the second type but in both cases the potential gains with respect to the basic "bag of words" approach are substantial. Also, contrary to what is sometimes said, syntactic approaches are not any more subjective than "bag of words". In fact, surveys of methods of content analysis assign all of them to the family of "supervised approaches", indicating human involvement in their design. This is because the dictionaries, which are behind any "bag of words" analysis have to be created by humans. Even inductive algorithms offer a fair degree of inter-subjective reliability, because the learning sets are always evaluated by more than one person and the results of learning are only accepted when the agreement between the instructors and the machine but also among the instructors themselves reaches a certain, appropriately high threshold. In the News Analytics database this is reflected by three "tone probability" scores, which show how likely each news item was to receive one of the three tone labels: positive, neutral or negative (the one assigned is simply the one with the highest probability).

The basic building block of our aggregation is the news tone for company i on day t, which is computed as follows:

$$Tone_{i,t} = \sum_{k=1}^{kpos} 1 \cdot prob\_pos_{i,t,k} + \sum_{k=1}^{kneg} (-1) \cdot prob\_neg_{i,t,k}. \tag{4.1}$$

That is, all positive news items (indicated by +1) for company i on day t are multiplied by the probability of being classified as positive and summed and similarly for negative news items. Adding the two sums for positive and negative news produces a measure of the difference between the positive and negative content published about company i on day t. It will be positive if there were more positive news items and/or if the positive news items had a higher probability, *prob_pos*, attached to them, and negative otherwise. The greater the number of news about company i on day t the greater the potential magnitude of the news tone in the case of a significant imbalance between positive and negative news. For this reason companies with a lot of news flow are more likely to register very high or very low values of news tone.

Our first core measure captures the daily (D superscript below) level of aggregate news tone and makes use of the fact that the individual company tones in Eq. 4.1 are additive:

$$\begin{aligned} AggTone_t^D &= \sum_{i=1}^{n} Tone_{i,t} = \\ &= \sum_{i=1}^{n} \sum_{k=1}^{kpos} 1 \cdot prob\_pos_{i,t,k} + \sum_{i=1}^{n} \sum_{k=1}^{kneg} (-1) \cdot prob\_neg_{i,t,k} \end{aligned} \tag{4.2}$$

which is the daily imbalance between positive and negative news for all companies n, having news on day t. Thus, companies with a large news flow, that is big companies or those with important events going on, will generally contribute more to the aggregate measure, which is quite similar to using value weighting in constructing price indices and ensures that aggregate news tone is not driven by small, less relevant stocks. For the purpose of computing the daily aggregate tone, we use the period starting at 4pm on calendar day $t-1$ (i.e. yesterday's close) and ending at 3:45pm on calendar day t (i.e. 15 minutes before today's close). This ensures that our measure reflects the information available to an investor wishing to trade on news tone before the market closes on day t.[1]

While our measure of the level of aggregate news tone reflects the first moment of news tone, one could also imagine a measure which captures the second moment of news tone. Such a measure is important to consider since the level of aggregate news tone does not necessarily provide a complete picture of the current information flow. To see this, consider the following two situations: (1) there is little news overall, i.e. not much information is entering the market, (2) there are a lot of highly polarized news items where companies with positive news items are offset by companies with negative news. Both cases produce an aggregate level of news tone close to zero although they are admittedly very different from the viewpoint of investors. For an investor wanting to form an opinion about the aggregate market using firm-specific news, the first case represents few signals overall while the second case represents a large number of contradictory signals. In the latter case, each firm-specific signal can be precise but aggregating a dispersed set of signals produces high uncertainty about the aggregate market. To account for these possibilities, we supplement our level measure of news tone with a measure of daily news tone dispersion, defined as the standard deviation of firm-specific news tones at date t :

$$AggDisp_t^D = Std(Tone_{i,t}) \tag{4.3}$$

We also construct monthly level and dispersion measures. The monthly (M superscript below) aggregate level of news tone is simply the sum of daily aggregate levels during that particular month.

$$AggTone_t^M = \sum_{t=1}^{T}(AggTone_t^D), \tag{4.4}$$

where T equals the number of days in a given month. The monthly news tone dispersion is constructed by first computing monthly measures of firm-specific news tones, done by summing all daily news tone observations within each month for each company i, and then

[1] It makes little difference to our results if one instead uses close-to-close information.

taking the standard deviation of these monthly firm-specific news tones:

$$AggDisp_t^M = Std(\sum_{t=1}^{T} Tone_{i,t}), \tag{4.5}$$

where T again equals the number of days in a given month.

Figures 4.1 and 4.2 plot the dynamics of the daily and monthly measures of the aggregate level and dispersion of news tone for our sample period January 2003 to December 2011. We have winsorized the series at the 1st and 99th percentiles in order to mitigate the influence of large outliers. We have then standardized all series by demeaning and dividing by the standard deviation, in order to ease the interpretation. Two things are apparent from the pictures. First, the level of aggregate news tone (upper panel in both figures) exhibits substantial variation over time. The aggregate news tone increased leading up to the onset of the financial crisis in mid-2007, then dropped sharply in 2008 and rebounded in 2009. The renewed sharp drop in news tone in 2011 coincides with the European sovereign debt crisis. Second, the level and dispersion (lower panel in both figures) of news tone appear negatively correlated. Dispersion is generally low when tone is increasing and registers several large spikes when tone is at its lowest. This is reminiscent of the asymmetric volatility effect (e.g., Bekaert and Wu (2000)) and suggests that high volatility in bad times might be partly due to contradictory company news. This link becomes even more suggestive when aggregate tone and dispersion (at the monthly frequency) are plotted against the most popular measure of expected volatility, the VIX index (Figure 4.3). The apparent negative correlation between aggregate tone and the VIX and the positive correlation between aggregate dispersion and the VIX persists not only during the financial crisis but also before and after. In fact, the graph suggests that aggregate dispersion leads the VIX by one month, in particular for the large changes during the sample period.

Since we are interested in understanding whether soft firm-specific information matters beyond hard information, we include a broad range of variables which reflect economic and financial conditions. The first is the variance risk premium (VP), defined as the difference between implied and realized variance, and which is often interpreted as a measure of economic uncertainty. Bollerslev, Tauchen, and Zhou (2009) demonstrate that the variance risk premium has predictive power for stock returns in excess of traditional predictors such as price-earnings ratios. As a monthly measure of economic activity we use the Chicago-Fed National Activity index which is obtained from the Federal Reserve Bank of St. Louis. Diether, Malloy, and Scherbina (2002) and Park (2005) show the importance of dispersion of earnings forecasts as a proxy for different expectations of fundamentals at the individual and aggregate level respectively. Following Park (2005) we obtain the dispersion of 12-month-ahead forecasts for the aggregate earnings of S&P 500 firms from IBES. We also use information on the actual aggregate earnings of S&P 500 firms. Data on the VIX index is downloaded from Datastream. The Aruoba-Diebold-Scotti Business Conditions Index (ADS) is used as it measures economic activity on a daily basis and is obtained from the Federal Reserve Bank of Philadelphia. The University of Michigan sentiment index is retrieved from Datastream. We also consider abnormal turnover which is computed as follows. First, we compute turnover as the ratio of daily shares volume and shares outstanding. To reduce the skewness of the turnover distribution we use logarithms and to avoid the problem of zero turnover we follow the method applied in Llorente, Michaely, Saar, and Wang (2002) and add a small positive constant to each raw turnover value.[2] We then compute abnormal turnover as the difference between log turnover on day t and a 60-day moving average of log turnover. Finally, we relate the level and dispersion of aggregate news tone to the investor sentiment measures obtained from the website of Jeffrey Wurgler.

Aggregate stock market returns are measured using returns on the widely traded exchange traded fund that tracks S&P 500, SPY, and which represents returns that are obtainable by investors in practice. The returns are obtained from Datastream. Daily and monthly excess returns are computed using Fama's one-month Treasury-bill rate obtained from CRSP. For computing daily excess returns, we assume that the one-month rate is constant within each month. We also use daily and monthly data on the realized variance of the S&P500 downloaded from the data library of the Oxford-Man Institute and from the website of Hao Zhou respectively (see Zhou (2010)). We also consider information potentially contained in past prices. Apart from lagged values of returns and volatilities, we construct a measure of return dispersion, which mimics the news dispersion introduced earlier. It is the cross-sectional standard deviation of returns (either daily or monthly) of all constituents of the S&P 500 index. Thus, we can control whether the dispersion in news tone merely reflects the fact that some companies were performing well and others poorly in the past.

Table 4.1 reports summary statistics of our daily variables and daily correlations between our two news tone measures and remaining variables. The table shows that both the level and dispersion of aggregate news tone exhibit excess kurtosis but the level of news tone is negatively skewed whereas the dispersion measure is positively skewed. Both measures are subject to similar persistence with daily autocorrelation coefficients of 0.70 and 0.66 for level and dispersion respectively. The second panel demonstrates that the daily level and dispersion measures are negatively correlated, -0.27. Interestingly, both measures are significantly correlated with realized and implied volatility (VIX). A higher aggregate tone is associated with lower stock return volatility while higher dispersion is linked to higher

[2]The magnitude of this constant, 0.00000255, is chosen as to make the distribution of turnover closer to normal (e.g., Richardson, Sefcik, and Thompson (1986).

volatility.

Table 4.2 reports monthly summary statistics and correlations. The monthly skewness and kurtosis of the two tone measures are similar to their daily values while the persistence of tone level is higher than that for dispersion, 0.84 versus 0.51 in first-order autocorrelation coefficients. The persistence decays to around 0.30 for both measures when using five lags. The second panel demonstrates that the level and dispersion measures are highly negatively correlated, -0.50, and have opposite relations to stock returns and volatility. While the level of news tone is positively related to stock returns and negatively related to volatility, higher dispersion is instead related to lower returns and higher volatility. The two news tone measures also carry significant correlations with a range of economic variables. Higher news tone is associated with higher economic activity, higher consumer sentiment, lower turnover, lower dispersion of earnings forecasts, and positive changes to realized earnings. On the other hand, higher dispersion of news tone implies the opposite sign in correlations. Simply put, higher level of news tone indicates good economic times, high returns, and low volatility while higher dispersion indicates bad economic times, low returns, and high volatility.

In Table 4.3, we relate our news tone variables to the four investor sentiment measures used in Baker and Wurgler (2006) and Baker and Wurgler (2007). Interestingly, the magnitude of the correlation coefficients are all low and significantly lower than correlations between news tone and the economic variables presented earlier. A possible interpretation is that the aggregate level and dispersion of news tone more reflect rational market forces rather than irrational or sentimental factors.

4.3 Empirical Analysis

The last section demonstrated that the level and dispersion of news tone are contemporaneously related to returns, volatility, and various economic and financial variables. In this section, we analyze whether our news tone measures, which quantify ”soft” company-specific information, carry any incremental information beyond ”hard” data. In order to do so, we test whether our news tone measures have any predictive power for aggregate stock returns, realized variance, and the variance risk premium, controlling for various economic and financial variables. We run both daily and monthly regressions using various specifications. We consider three specifications for each dependent variable. The first specification uses the aggregate level and dispersion of news tone as independent variables. The second specification uses a number of variables capturing hard information, reflecting current economic and financial conditions and the third specification includes all variables jointly, resulting in a ”horse race” between soft and hard information.

4.3.1 Predicting Aggregate Stock Returns

Dependent variables for the return regressions are daily and monthly excess returns on the S&P 500, measured by the widely traded exchange-traded fund SPY. Table 4.4 presents results from predicting daily excess stock returns. The first column indicates that the dispersion of news tone predicts returns negatively with a statistically significant coefficient. Since the tone measures are standardized, the regression coefficient implies that a one standard deviation increase in dispersion predicts a decrease in returns of 9 basis points the next day. The R^2-value is 0.34% which might seem small but which is non-negligible for a daily horizon. The second column presents results from predicting returns with changes in the ADS index, the VIX index, and past returns. Past returns predict returns with a significant negative coefficient indicating mean reversion in daily returns. The R^2-value is 1.62%. The third column presents results from including all variables jointly. The dispersion measure turns out highly statistically significant and the R^2-value increases, indicating that aggregate dispersion of news tone matters. It is also not subsumed by return dispersion, indicating that past returns do not fully reflect past news.

Table 4.5 presents results from predicting monthly excess returns. The first column demonstrates that monthly dispersion of news tone carries predictive power for future returns with a statistically significant coefficient of -1.40. This implies that a one standard deviation increase in monthly dispersion predicts a drop in returns of 1.40% next month. The monthly R^2-value is 6.37%. The second column shows that predicting monthly returns with a range of economic and financial variables yields a lower R^2-value and statistically insignificant coefficients. Including all variables jointly increases the explanatory power and produces only one statistically significant coefficient, the dispersion of news tone.

4.3.2 Predicting Realized Variance

This section presents results from predicting the daily and monthly realized variance of S&P 500 returns. Table 4.6 presents results from the daily regressions. The first column indicates that both the level and dispersion of news tone matter for future volatility since both regression coefficients are highly significant. The results show that the level and dispersion have opposite effects on volatility. Higher news tone predicts lower volatility while higher news dispersion predicts higher volatility. The second column shows that past volatility and returns have great predictive power for future volatility. Including all variables jointly renders the news tone variables insignificant. Hence, while daily aggregate news tone predicts daily future volatility with significant coefficients, the two aggregate news tone measures seem to carry no extra information beyond lagged volatility and returns.

Next, we predict monthly realized variance of stock returns. Table 4.7 shows that the two news tone measures predict realized variance with a R^2 value of almost 42% and with both coefficients highly significant. As with daily data, higher level (dispersion) predicts volatility negatively (positively). The second column demonstrates that predicting volatility with only economic and financial variables produce similar explanatory power as with the tone measures. Interestingly, higher economic activity measured by the Chicago Fed Index (Fed) predicts volatility negatively. Results from including all variables jointly suggest that the dispersion of news tone adds information in excess of the other variables. The coefficient on dispersion is positive and highly significant, and the explanatory power increases to around 53%.

Overall, the predictability results indicate that the level and dispersion of news tone have predictive power in excess of economic and financial variables. The dispersion measure in particular seems to contain important information for returns and volatility. The results suggest that more contradictory company news across firms predicts low returns and high volatility, indicating that aggregate information uncertainty matters for equity prices.

4.3.3 Predicting the Variance Risk Premium

The fact that dispersion of company news tone is a significantly positive predictor of market volatility supports its interpretation as a measure of economic uncertainty. At the same time, negative news are associated with an increase in volatility (the well known asymmetric volatility effect), suggesting an inverse relationship between the level of news tone and information uncertainty. To examine this intuition more closely, we relate our measures to the variance risk premium (VP), originally put forward by Bollerslev, Tauchen, and Zhou (2009). It is computed at the end of each month t as the difference between forward-looking volatility for month $t + 1$, implied from prices of index options on the S&P 500 (approximated in a model-free way using the VIX), and backward-looking realized volatility for month t, computed as the sum of squared high-frequency returns on the same index.

The variance risk premium has often been interpreted as a measure of economic uncertainty. We are interested in understanding how the variance risk premium relates to the level and dispersion of aggregate news tone. If the variance risk premium reflects current uncertainty, then it could presumably be interpreted as an indirect measure of current information uncertainty. In contrast, by aggregating and quantifying the tone of company news, we are able to provide a direct measure of information uncertainty, potentially leading the variance risk premium.

We start by analyzing lead-lag correlations between the variance risk premium and the aggregate level and dispersion of news tone in Figure 4.4. In both panels of the figure, the variance risk premium is held constant at time t while we vary the news tone measures.

For example, the lead-lag correlation at horizon -5 refers to the correlation between the variance risk premium at time t and news tone at time $t-5$. The results seem to confirm our intuition. The top figure shows that the aggregate level of news tone leads the variance risk premium with a negative sign indicating that a drop in the level of news tone signals an increase in future variance risk premiums. For positive horizons, the correlations quickly go towards zero suggesting that the variance risk premium has a lower ability to lead the level of news tone than vice versa. The bottom figure demonstrates that the aggregate dispersion of news tone also has the ability to lead movements in the variance risk premium. Higher dispersion in company news signals higher future variance risk premiums. Again, correlations for positive horizons go towards zero suggesting the variance risk premium only leads dispersion of company news to a small extent. These findings suggest that our news tone measures should have predictive power for future variance risk premiums.

We test this by running monthly predictive regressions using the variance risk premium as dependent variable. The results are reported in Table 4.8 and indicate that both measures of news tone significantly predict the variance risk premium, both having the expected sign. Higher level of news tone predicts a lower future variance risk premium, while higher dispersion of news tone predicts an increase in the variance risk premium. This suggest that direct ways of measuring information and information uncertainty, as in our news tone variables, predict future values of more indirect measures such as the variance risk premium. Moreover, the effect of news tone is not subsumed by the control variables, even though news dispersion loses some of its initial significance (now significant on the 10%-level). Overall, the results support the notion of the level and dispersion of aggregate news tone as being direct measures of information and information uncertainty.

4.4 Conclusions

We demonstrate that the tone of firm-specific news has systematic effects on the prices of not only individual stocks but also the market indices. Using a large data base in which the language of millions of individual news items has been quantified, we use a bottom-up approach and construct two novel measures: The aggregate *level* of news tone and the aggregate *dispersion* of news tone. We find that a higher level of aggregate news tone is associated with higher economic activity, higher aggregate returns, and lower aggregate stock volatility, while the aggregate dispersion of news tone has the opposite effects. We interpret the aggregate level and dispersion of news tone as high-frequency measures of economic conditions and economic uncertainty.

Importantly, both the level and dispersion of aggregate news tone predict future aggregate stock returns, volatility, and variance risk premiums, controlling for a host of macroeconomic and fundamental variables. Thus, quantifying the language of company-specific news carries valuable information about the aggregate stock market, not contained in hard data. However, this does not mean that news tone represents irrational investor sentiment. In fact, it is only weakly correlated with the sentiment index of Baker and Wurgler (2006). Instead, we argue it represents the "soft" part of fundamentals, reflecting the overall level and uncertainty about company information, driving rational investor uncertainty.

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Table 4.1: Daily Summary Statistics and Correlations

	Daily Summary Statistics					
	Mean	Std	Skewness	Kurtosis	AC(1)	AC(5)
$AggTone^D$	184	228	–0.89	6.28	0.70	0.68
$AggDisp^D$	2.22	0.77	3.69	39.01	0.66	0.51
SP500 Ret	0.02	1.36	–0.29	12.72	–0.12	–0.05
SP500 RV	1.41	3.25	9.73	164	0.69	0.57
VIX	21.3	10.29	2.05	8.59	0.98	0.95
ΔADS	0.00	0.03	–0.11	17.70	0.65	0.78
DispRet	1.84	0.92	2.83	10.7	0.78	0.72

	Daily Correlations						
	$AggTone^D$	$AggDisp^D$	SP500 Ret	SP500 RV	VIX	ΔADS	DispRet
$AggTone^D$	1.00	–0.27	0.04	–0.42	–0.60	–0.01	-0.52
$AggDisp^D$	–0.27	1.00	–0.03	0.27	0.40	0.05	0.38

The table reports daily summary statistics for the sample period Jan 2003-Dec 2011. $AggTone^D$ is calculated daily as the weighted difference of positive and negative news about US companies. $AggDisp^D$ is the cross-sectional standard deviation of $Tone$, which is calculated daily for each company separately. SP500 Ret, SP500 RV and VIX are the daily return, daily realized volatility and daily implied volatility of the S&P 500 respectively. ΔADS is the daily change in the economic activity index of Aruoba, Diebold, and Scotti (2009)

Table 4.2: Monthly Summary Statistics and Correlations

	Monthly Summary Statistics					
	Mean	Std	Skewness	Kurtosis	AC(1)	AC(5)
AggTone^M	3828	3879	–0.97	3.73	0.84	0.30
AggDisp^M	8.04	3.66	3.32	20.00	0.51	0.32
SP500 Ret	0.34	4.44	–0.86	5.30	0.24	–0.04
SP500 RV	29.72	55.42	5.70	43.08	0.36	0.20
Fed	–0.36	1.04	–1.92	6.97	0.80	0.62
VIX	21.22	9.55	1.64	6.08	0.87	0.49
Michigan	79.27	12.4	–0.20	1.86	0.93	0.78
ΔEarn	0.42	2.48	0.09	11.78	–0.05	0.01
DispEarn	0.29	0.10	1.42	4.46	0.92	0.72
VP	15.59	16.55	2.08	8.06	0.30	0.16
DispRet	8.18	2.93	2.24	6.40	0.65	0.55

	Monthly Correlations											
	AggTone^M	AggDisp^M	SP500 Ret	SP500 RV	Fed	VIX	Michigan	Turnover	EarnDisp	ΔEarn	VP	DispRet
AggTone^M	1.00	–0.50	0.26	–0.62	0.61	–0.71	0.40	–0.48	–0.33	0.23	–0.36	–0.72
AggDisp^M	–0.50	1.00	–0.31	0.53	–0.58	0.70	–0.68	0.53	0.53	–0.21	0.42	0.54

The table reports monthly summary statistics and correlations for the sample period Jan 2003-Dec2011. Michigan is the University of Michigan sentiment index. ΔEarn is the monthly change in aggregate 12-month trailing earnings of companies in the S&P 500. DispEarn is the dispersion in analyst forecast of aggregate earnings of S&P 500 companies in the next 12 months. VP is the variance risk premium. All other variables are monthly versions of variables defined in Table 4.1.

Table 4.3: Correlations with Baker-Wurgler Investor Sentiment

	$Sent^{\perp}$	$Sent$	$\Delta Sent^{\perp}$	$\Delta Sent$
AggTone^M	0.19	0.22	0.13	–0.25
AggDisp^M	0.16	–0.02	–0.28	0.04

The table shows unconditional correlations coefficients between our aggregate measures of news tone and investor sentiment factors computed by Baker and Wurgler (2006, 2007). *Sent* is computed as the first principal component of six variables (closed-end fund discount, the number of IPOs, first-day returns on IPOs, equity share in new issues, abnormal turnover and dividend premium) and $Sent^{\perp}$ is additionally orthogonalized with respect to several macroeconomic variables. $\Delta Sent$ and $\Delta Sent^{\perp}$ are computed as the first principal component of the *changes* in the abovementioned variables. The investor sentiment data is taken from the website of Jeffrey Wurgler which also contains descriptions of the variables. The sample period is 2003-2010.

Table 4.4: Predicting Daily Stock Returns

	Ret(t+1)	Ret(t+1)	Ret(t+1)
$\text{AggTone}^D(t)$	0.00		0.05
	(-0.08)		(1.47)
$\text{AggDisp}^D(t)$	-0.09		-0.10
	(-3.01)		(-3.37)
ΔADS(t)		-1.86	-1.78
		(-1.68)	(-1.61)
VIX(t)		0.01	0.01
		(1.56)	(2.59)
Ret(t)		-0.09	-0.09
		(-4.36)	(-4.34)
Ret(t-1)		-0.09	-0.08
		(-4.13)	(-4.01)
DispRet(t)		-0.08	-0.05
		(-1.85)	(-1.12)
$R^2_{adj}(\%)$	1.62	1.73	2.24

T-statistics are in parentheses and are computed using Newey-West (1987) with 10 lags. Dependent variable is the daily excess return on the S&P 500 exchange traded fund SPY.

Table 4.5: Predicting Monthly Stock Returns

	Ret(t+1)	Ret(t+1)	Ret(t+1)
$\text{AggTone}^M(t)$	-0.22		-0.53
	(-0.46)		(-0.74)
$\text{AggDisp}^M(t)$	-1.33		-1.27
	(-2.77)		(-2.31)
Fed(t)		0.88	0.73
		(1.26)	(1.03)
ΔEarn(t)		-0.14	-0.14
		(-0.74)	(-0.75)
DispEarn(t)		-5.78	-1.26
		(-0.87)	(-0.17)
VP(t)		0.08	0.09
		(2.62)	(2.77)
Ret(t)		0.27	0.23
		(2.49)	(2.06)
DispRet(t)		-0.01	-0.06
		(-0.03)	(-0.20)
$R^2_{adj}(\%)$	5.98	9.15	12.19

T-statistics are in parentheses and are computed using Newey-West (1987) with 5 lags. Dependent variable is the one-month excess return on the S&P 500 exchange traded fund SPY.

Table 4.6: Predicting Daily Realized Variance

	RV(t+1)	RV(t+1)	RV(t+1)
$\text{AggTone}^D(t)$	-1.15		0.06
	(-17.98)		(1.05)
$\text{AggDisp}^D(t)$	0.53		0.00
	(8.20)		(0.07)
ΔADS(t)		-1.11	-1.14
		(-0.67)	(-0.69)
VIX(t)		0.05	0.06
		(7.77)	(7.48)
RV(t)		0.23	0.23
		(10.95)	(10.91)
RV(t-1)		0.35	0.35
		(17.60)	(17.51)
Ret(t)		-0.46	-0.46
		(-13.86)	(-13.85)
Ret(t-1)		-0.23	-0.23
		(-7.30)	(-7.31)
DispRet(t)		0.36	0.37
		(5.02)	(5.05)
$R^2_{adj}(\%)$	18.39	63.18	63.17

T-statistics are in parentheses and are computed using Newey-West (1987) with 10 lags.Dependent variable is the daily realized variance of the S&P 500 obtained from the Oxford Man Institute.

Table 4.7: Predicting Monthly Realized Variance

	RV(t+1)	RV(t+1)	RV(t+1)
$\text{AggTone}^M(t)$	-15.44		-5.27
	(-3.27)		(-0.77)
$\text{AggDisp}^M(t)$	26.14		20.53
	(5.53)		(4.03)
Fed(t)		-11.38	-8.28
		(-1.56)	(-1.21)
ΔEarn(t)		0.65	0.47
		(0.36)	(0.28)
DispEarn(t)		-7.85	-15.47
		(-0.12)	(-0.22)
VP(t)		-0.07	-0.16
		(-0.23)	(-0.55)
RV(t)		0.37	0.33
		(3.05)	(2.92)
RV(t-1)		-0.19	-0.28
		(-1.80)	(-2.70)
Ret(t)		-3.15	-2.25
		(-2.61)	(-1.97)
DispRet(t)		4.63	2.05
		(1.88)	(0.72)
$R^2_{adj}(\%)$	41.89	45.16	52.19

T-statistics are in parentheses and are computed using Newey-West (1987) with 5 lags. Dependent variable is the realized variance of S&P 500 returns obtained from the website of Hao Zhou.

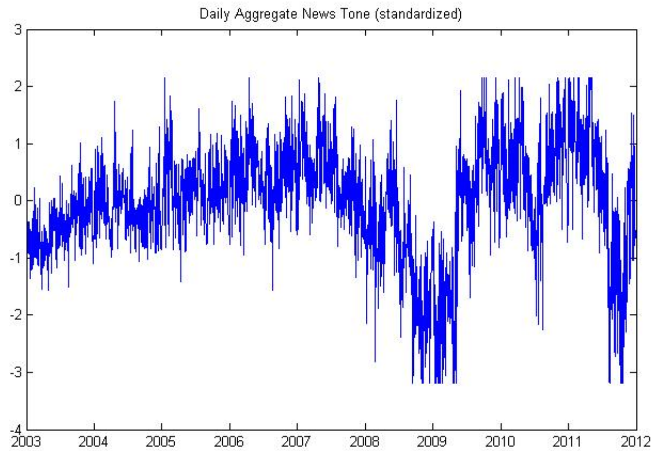
Table 4.8: Predicting Monthly Variance Risk Premia

	VP(t+1)	VP(t+1)	VP(t+1)
$\text{AggTone}^M(t)$	-4.39		-8.04
	(-2.73)		(-3.72)
$\text{AggDisp}^M(t)$	5.23		3.38
	(3.25)		(2.01)
Fed(t)		-1.96	0.68
		(-0.85)	(0.31)
ΔEarn(t)		1.11	0.88
		(1.82)	(1.56)
DispEarn(t)		77.05	109.40
		(3.54)	(4.81)
VP(t)		-0.05	-0.10
		(-0.48)	(-1.04)
Ret(t)		-0.49	-0.06
		(-1.39)	(-0.18)
DispRet(t)		0.14	-2.45
		(0.18)	(-2.56)
$R^2_{adj}(\%)$	24.07	26.46	38.43

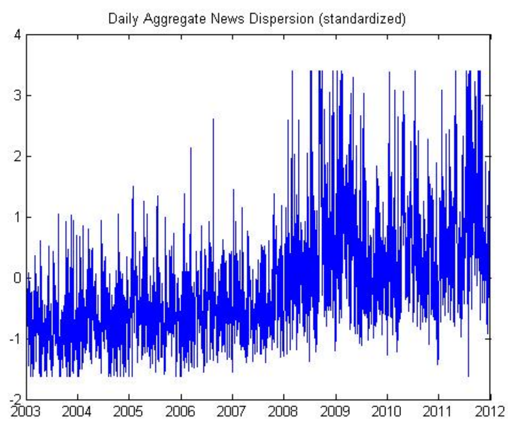
T-statistics are in parentheses and are computed using Newey-West (1987) with 5 lags. Dependent variable is the monthly variance risk premium obtained from the website of Hao Zhou.

Figure 4.1: Quantitative measures of company news flow - daily frequency

(a) Aggregate news tone level



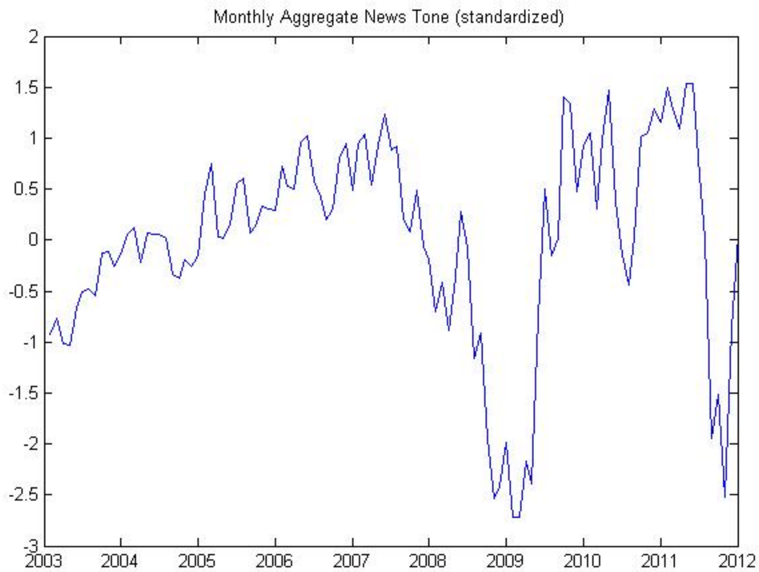
(b) Aggregate news tone dispersion



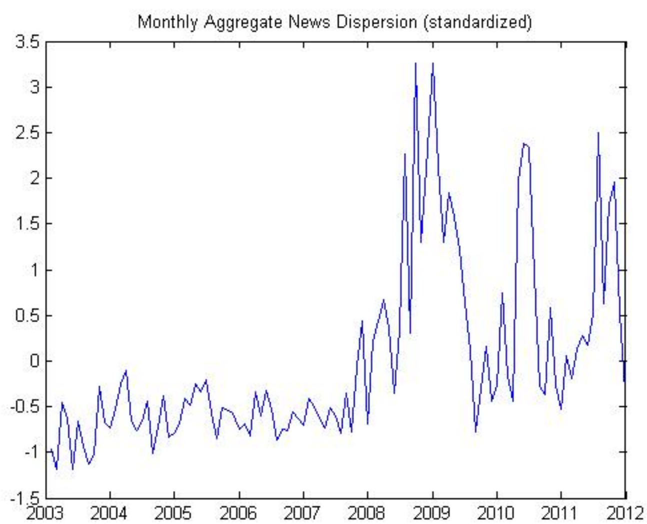
Plotted are daily aggregates of news about US companies, retrieved from Thomson Reuters News Analytics for the period 2003 - 2011. Definitions of daily aggregate news tone level and aggregate news tone dispersion are discussed in Section 2 and are explicitly given in Eq. 4.2 and Eq. 4.3 respectively. Both time series are shown in standardized form.

Figure 4.2: Quantitative measures of company news flow - monthly frequency

(a) Aggregate news tone level



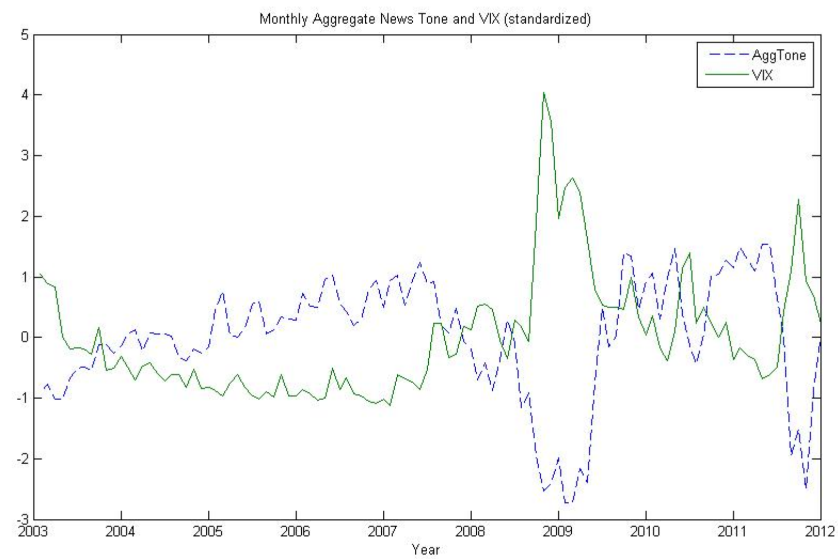
(b) Aggregate news tone dispersion



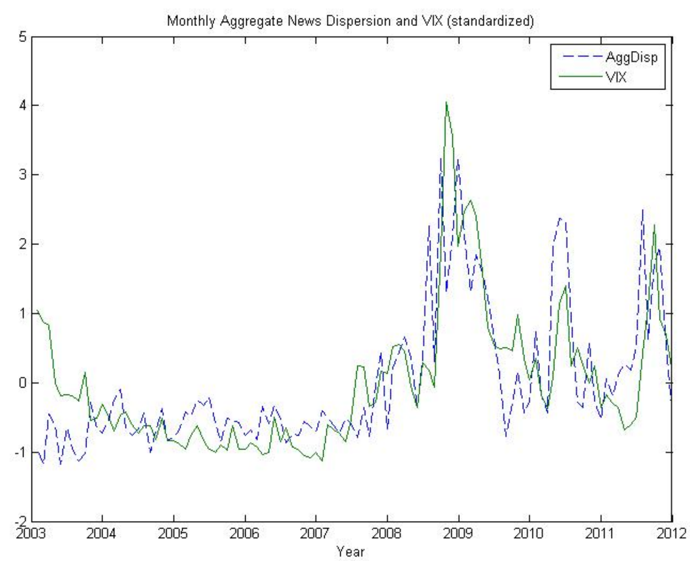
Plotted are monthly aggregates of news about US companies, retrieved from Thomson Reuters News Analytics for the period 2003 - 2011. Definitions of monthly aggregate news tone and aggregate dispersion of news tone are discussed in Section 2 and are explicitly given in Eq. 4.4 and Eq. 4.5 respectively. Both time series are shown in standardized form.

Figure 4.3: Monthly measures of company news flow and the VIX

(a) Aggregate news tone level and the VIX



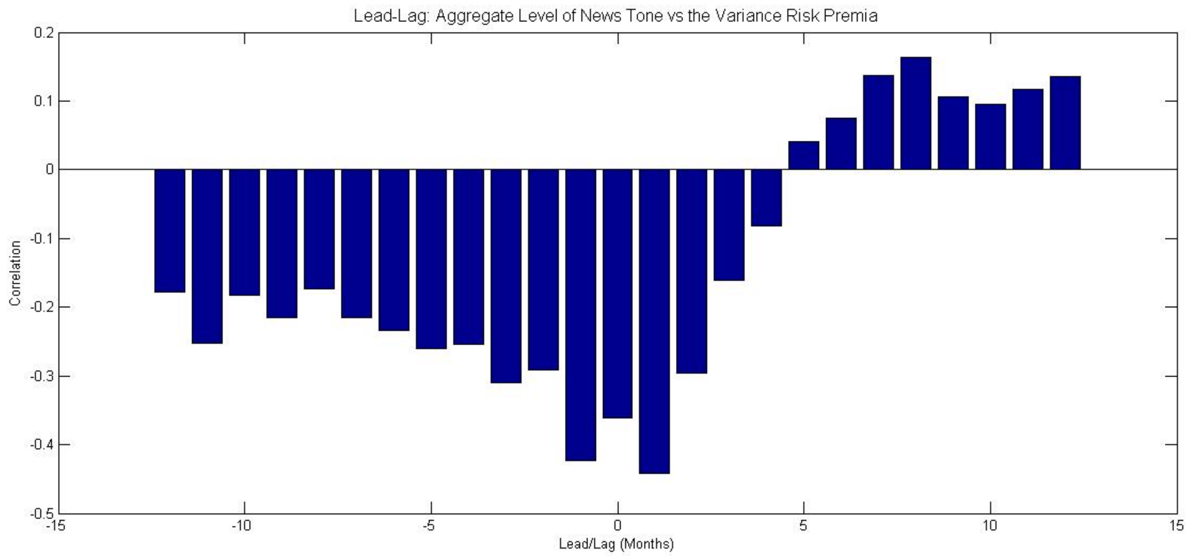
(b) Aggregate news tone dispersion and the VIX



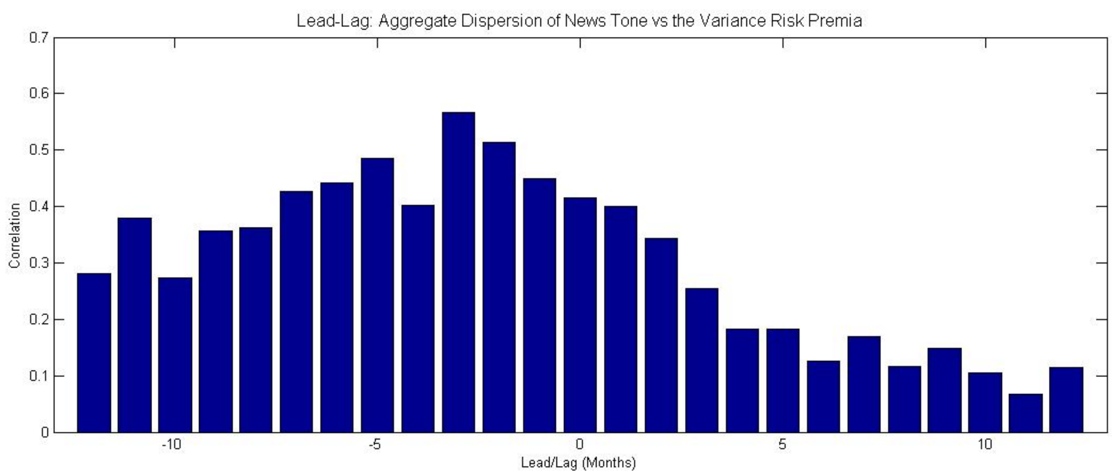
Monthly measures of company news flow from Figure 4.2 are plotted (in blue, dashed line) against end-of-month levels of the VIX (in green, solid line) for the period 2003 - 2011. Both time series are shown in standardized form.

Figure 4.4: Lead-Lag Analysis between News Tone and the Variance Risk Premium

(a) Aggregate level of news tone and the variance risk premium



(b) Aggregate dispersion of news tone and the variance risk premium



The figures present lead-lag correlations between measures of aggregate news tone and the variance risk premium on $S\&P$ 500. The top figure presents correlations between the aggregate level of news tone and the variance risk premium, where the variance risk premium is held fixed at time t while the news tone measure is varied. For example, a lead/lag horizon of -5 refers to the correlation between aggregate level of news tone at time $t-5$ and the variance risk premium at time t. The bottom figure presents correlations between the aggregate dispersion of news tone and the variance risk premium, where the variance risk premium is held fixed at time t while the news tone measure is varied. For example, a lead/lag horizon of -5 refers to the correlation between aggregate dispersion of news tone at time $t-5$ and the variance risk premium at time t. We consider lead/lag horizons of -12 months to +12 months. Time period is Jan 2003-Dec 2011.

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Erasmus Scholarship, University of Zurich **Oct 2006 – Jul 2007**

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PROFESSIONAL EXPERIENCE

Polish Financial Supervision Authority, Warsaw, Poland
Analyst **Nov 2008**
My task when working with the Financial Stability Group was monitoring and summarizing the suggested solution to the global financial crisis

McKinsey & Company, Warsaw, Poland (Kiev, Ukraine)
Business Analyst **Jul 2007 – Oct 2007**
I was working with a team of consultants on an engagement focused at assisting the Ukrainian government in organizing EURO 2012 football championship

Polish Constitutional Tribunal, Warsaw, Poland
Legal intern **Aug 2005**
I was involved in preparing drafts of Tribunal's rulings in the preliminary control procedure and preparing drafts of other legal correspondence